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Strategies for climate change mitigation: policy and technological considerations

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Declaration of Authorship

I, Geoffroy DOLPHIN, declare that this thesis titled, “Strategies for climate change mitigation: policy and technological considerations” and the work presented in it are my own. I confirm that:

- This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration, except as declared hereunder and specified in the text.
- It is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. I further state that no substantial part of my dissertation has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared hereunder and specified in the text.
- Chapter 2 was written in collaboration with Prof. Michael Pollitt and Prof. David Newbery. I contributed 85% of the development of this chapter. Their respective contribution amounted to 10% and 5%. Chapters 3 and 4 were written in collaboration with Prof. Michael Pollitt, who contributed 10%.
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UNIVERSITY OF CAMBRIDGE

Abstract

Judge Business School, University of Cambridge

Doctor of Philosophy

Strategies for climate change mitigation: policy and technological considerations

by Geoffroy DOLPHIN

The present thesis addresses the policy and technological aspects of national (and sub-national) greenhouse gases (GHG) abatement strategies. Two of the three chapters of this thesis explore the former, respectively investigating (i) domestic political economy constraints and (ii) processes of policy diffusion across jurisdictions. One chapter focuses on the latter, advancing methodologies for the identification of firm-level innovation in (GHG-reducing) electricity supply technologies.

A key empirical contribution of this thesis, presented in the first chapter, is the construction and calculation of an average (emissions-weighted) price of carbon for the jurisdictions under study, which shows, among other insights, that the world average price remains extremely low, at about 1.5USD/tCO2e in 2018. In addition, the analysis in this chapter suggests that (i) political economy factors primarily affected policy implementation and (ii) policy stringency is a highly persistent process.

Our next chapter investigates policy diffusion processes and proposes that these are related to an alteration of the net payoffs of domestic climate policy and an update on the information about the benefits (or costs) of policy adoption derived from the adoption of a similar policy or the deployment of abatement technology in foreign jurisdictions. The evidence suggests that technology demonstration and learning from past policy experience positively affect (domestic) policy developments.

The last chapter focuses on the identification of (GHG-abating) electricity supply technologies using a machine learning search strategy based on patents' title and abstract. This approach highlighted the role of "lateral" innovation in the development of some electricity generation technologies. In addition, by linking the identified patent set to legal entities, we uncover the role of firms' technological entry and exit in technology transition and shed light on the business structure of technologically active entities.

The present work allowed me to address fundamental questions pertaining to the design of climate change mitigation strategies. First, our results stress the importance of the sequence of introduction of the climate policies, suggesting that policies weakening incumbents' political and economic influence might foster subsequent implementation of more stringent policies. Second, given the weakness of most existing carbon pricing schemes, a rationale for the development of climate mitigation strategies with multiple GHG abatement tools continues to exist. Third, mechanisms of policy diffusion at play could prove highly valuable when seeking to introduce carbon-pricing mechanisms in new jurisdictions. Finally, we point at the need to target public support to sustain the stream of GHG-abating electricity supply technologies primarily at new (technological) entrants.

“Pour ce qui est de l’avenir, il ne s’agit pas de le prévoir, mais de le rendre possible.”

Antoine de Saint Exupéry

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As I was preparing to (temporarily) "abandon" the present thesis, I couldn't help but notice the strange similarities between the process that led to its creation and the opening scene of Francis Ford Coppola's *Apocalypse Now*. One of the longest in the history of modern cinema, it depicts the napalm ravaged forests of Vietnam and a mentally tortured Captain Benjamin Willard to the tune of a confusing *The End* by The Doors. After three and a half years of work, I have, I believe, reached The End of the Opening.

The completion of this journey owes much to many people around me. First and foremost, I express my most profound gratitude to my supervisor Prof. Michael Pollitt, whose guidance and unwavering support have been instrumental to the advancement of the work contained in this thesis. In addition, his generosity and kindness contributed to make the PhD process an enjoyable experience.

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Finally, I have enjoyed the extraordinary privilege of both a loving family and caring friends. For that, I will be forever grateful. They contributed no small part to this journey, from providing me with the comfort of a home base to fall back on, to a welcome introduction to Python, via the occasional-yet-much-needed trip to the pub. Their support was instrumental in ensuring that I don't end up as mentally troubled as Captain Willard.

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List of Abbreviations

CPC	**C**ooperative **P**atent **C**lassification
CRS	**C**onstant **R**eturns to **S**cale
EC	**E**lectricity **C**ouncil
ECP	**E**missions-weighted **C**arbon **P**rice
ESI	**E**lectricity **S**upply **I**ndustry
ETS	**E**missions **T**rading **S**cheme
EU	**E**uropean **U**nion
EU-ETS	**E**uropean **U**nion **E**missions **T**rading **S**ystem
EUA	**E**uropean **U**nion **A**llowance
FF	**F**ossil **F**uel electricity generation technologies
GDP	**G**ross **D**omestic **P**roduct
GHG	**G**reenhouse **G**ases
GMM	**G**eneralised **M**ethod of **M**oments
INDC	**I**ntended **N**ationally **D**etermined **C**ontribution
IPC	**I**nternational **P**atent **C**lassification
IPCC	**I**ntergovernmental **P**anel on **C**limate **C**hange
ISIC	**I**nternational **S**tandard **I**ndustrial **C**lassification
OEMs	**O**riginal **E**quipment **M**anufacturers
ODA	**O**fficial **D**evelopment **A**ssistance
OECD	**O**rganisation for **E**conomic **C**ooperation and **D**evelopment
OFGEM	**O**ffice **F**or **G**as and **E**lectricity **M**arkets
REN	**R**enewable **E**nergy electricity generation technologies
RES	**R**enewable **E**nergy **S**upport
RGGI	**R**egional **G**reenhouse **G**ases **I**nitiative
ROW	**R**est **O**f the **W**orld
SCC	**S**ocial **C**ost of **C**arbon
UK AEA	**U**nited **K**ingdom **A**tomic **E**nergy **A**uthority
UK IPO	**U**nited **K**ingdom **I**ntellectual **P**roperty on **O**ffice
UNFCCC	**U**nited **N**ations **F**ramework **C**onvention on **C**limate **C**hange

To Rach and Max, who, in their own ways, kept me grounded

Chapter 1

Introduction

The unprecedented accumulation of greenhouse gases (GHGs) in the atmosphere poses a monumental challenge to humanity. As ever greater amounts of heat get trapped, global and regional climate patterns change, affecting natural and human-created systems alike.

Past accumulation has already induced observable changes. In Western Europe, hotter and dryer summer seasons have slowly had the best of some Alpine glaciers (European Environment Agency, 2016). In regions exposed to tropical cyclones, model-based projections suggest they can expect more intense occurrences due to combined warming of sea and troposphere temperatures (Knutson et al., 2019) while longer and more frequent droughts in Central and Eastern Africa cause famine and make it harder to end extreme poverty (Roy et al., 2018).

Climate Change used to be thought of, at least in developed economies, as a geographically and temporally distant problem. Failure to reduce world emissions, especially over the last thirty years, has made it a “here" and “now" problem for most of the world’s population. And because of the lag between the level of GHG in the atmosphere and the equilibrium response of the climate system, there is always more than meets the eye: the present level locks us in for further changes and further accumulation, possibly at increasing rates, will induce changes that will only materialise later this century.

Yet, reducing emissions has so far proven difficult, not least because their main source, the combustion of fossil fuels, is now at the heart of our techno-economic system. Decades of development of industries based on their use as well as CO_2-releasing processes have created both technological and political path dependencies. From a technological standpoint, GHG-emitting technologies benefit from a long history of improvement and deployment at scale that makes them cheaper than newer, GHG-free ones. Politically, GHG-intensive sectors are the source of much income and wealth accumulation, making it hard for policy-makers to enact policies that would curb their activity, even temporarily.

These aspects would make the problem at hand hard enough to tackle if the world was a single, autarkic entity. It gets compounded when heat-trapping gases are emitted by multiple sovereign jurisdictions. When looking through that lens, one realises that GHG emissions create significant national (marginal) benefits but that most of the (marginal) burden falls onto areas and populations that lie beyond the borders of national policy makers’ constituencies. Hence, in the absence of genuine care for the global environment, the sum of local emissions levels far exceeds what would be globally optimal.

In the absence of a World government, tackling climate change therefore requires coordinated action. This is the *raison d'être* of the United Nations Framework Convention on Climate Change (UNFCCC) which, in its second article, commits its Parties to achieve "stabilisation of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system". The available evidence suggests that the multilateral climate change mitigation regime, developed over almost thirty years of existence of the UNFCCC, has fallen short of this objective: the current atmospheric CO_2 level, at about 408 ppm, is 1.45 time the value of a typical interglacial period (*The Economist*, Sept. 21-27, 2019).[1] Moreover, the latest data on global GHG emissions released by the Potsdam Climate Institute (Gutschow, Jeffery, and Gieseke, 2019) show that world yearly emissions have continued to rise steadily.[2]

The present situation can in part be attributed to the design of the Kyoto Protocol (KP), whereby only Annex I countries were committed to legally binding emissions reductions. As a result, emissions of Annex-I countries decreased by 12.4% between 1990 and 2017 while the emissions of the ten largest non Annex I countries were multiplied by a factor of 2.8 over the same period (Gutschow, Jeffery, and Gieseke, 2019).[3]

A compounding difficulty was that the KP offered a very static architecture with few provisions for (i) dynamic updates to Annex I countries' emissions reduction ambition or (ii) extension in participation by non-Annex I countries. Given the changes in technological and economic feasibility of emissions reduction over the lifetime of the Protocol, such provisions could have been extremely valuable. Moreover, this static nature combined with the fact that it was agreed by countries' respective international negotiations teams meant that it was brought from the *top, down* to national level policy makers but that there was little room for them to engage in (further) emissions reducing policy developments.

The latest iteration of formalised multilateral cooperation adopted under UNFCCC auspices, the Paris Agreement, took a notably different approach. First, it sought to remove the distinction made in the Kyoto Protocol and committed every Party – albeit in a non legally binding manner – to the same objective: limiting the increase in "[...] global average temperature to well below 2°C above pre-industrial levels and [pursue] efforts to limit the temperature increase to 1.5°C above pre-industrial levels [...]" (Paris Agreement, Art. 2-(a)).

Second, the Paris Agreement shifted the architecture of international climate negotiations from a cooperative to a non-cooperative setting: under its provisions, Parties are invited to

[1] For as long as the records from the Vostok ice core can tell, atmospheric CO_2 levels have fluctuated, usually between below 200 ppm at the end of glacial periods to just under 300 ppm during or soon after interglacial periods.

[2] During the period 2011-2016, GHG emissions (excluding land use, land-use change and forestry) grew on average at 0.52% per year, reaching 47Gt; in the five years prior to the 2008-2009 Great Recession, emissions grew on average at 3.05% per year. This, however, hides a more mixed regional picture. In the European Union (28), GHG emissions fell from 5.7Gt in 1990 to 4.4Gt in 2016, a 23% reduction. In the United States, unlike in the EU, yearly GHG emissions rose between 1990 and 2007, from 6.5Gt to 7.5Gt, and decreased steadily since then, reaching 6.6Gt in 2016. And yet another picture is observed in India and China: in India, yearly emissions rose steadily since 1990; in China's emissions had a similar growth rate until 2003, rose steeply in the run up to 2011, and have stabilised at around 12.5Gt between 2012 and 2016.

[3] As of 2017, the ten largest non Annex I emitters (GHG emissions excluding LULUCF) were, in order: China, India, Brazil, Indonesia, Mexico, Iran, Saudi Arabia, South Africa, Thailand, South Korea.

submit their Intended Nationally Determined Contributions (INDCs) to the achievement of the stated temperature warming objective. With such an institutional design, the key questions no longer pertain to the formation of climate coalitions and the mechanisms to sustain them but rather to the determinants of unilateral climate change mitigation policy ambition. In this respect, the Agreement implicitly acknowledges that technological demonstration and policy learning are such determinants. Indeed, parts of it rest on the premise that by offering to Parties the flexibility to put forward strategies based on a variety of abatement policies and technologies, it will foster their demonstration and diffusion across sectors and jurisdictions (Paris Agreement, Art. 6-1, 6-8, 7-6, 7-7, 10) and, ultimately, trigger increased climate policy ambition.

But given its non legally binding nature, whether or not the Paris Agreement triggers greenhouse gas (GHG) emissions reduction in line with the temperature warming objective depends on the Parties' self-determined pledges – the so called Intended Nationally Determined Contributions (INDCs) – and their commitment to implement them. Among the 60 NDCs assessed by the Climate Action Tracker, all but 7 fall short of the 2°C target and all but 2 (Morocco, The Gambia) fall short of the 1.5°C target (Hare and Höhne, 2019).

In other words, current world emissions level imply that we are fast depleting our 2°C carbon budget, making the case to strengthen the existing climate change mitigation regime clearer than it has ever been. This implies the need to break through both the political and technological inertia which have so far prevented the strengthening of incentives to reduce emissions as well as hindered the development and deployment of new GHG-free or GHG-abating technologies.

In an ideal world, this effort would be fully coordinated, establishing both a regulatory and technological level playing field. For instance, Parties to the Convention would agree on a common carbon price and embark on a technology development program whose outcomes would be openly accessible to all Parties.

Alas, reality is otherwise. Although some level of cooperation exists, national and subnational jurisdictions face strong incentives to deviate from fully cooperative frameworks. And because jurisdictions have structurally different economies and are host to constituencies with different preferences, these deviations have produced a patchwork of national and subnational initiatives, each amounting to varying degrees of emissions reduction ambition and the development of different abatement technology portfolios which, taken together, fall short of the collective target. That is, while the architecture of the Paris Agreement adopts a *bottom-up* approach and seeks to foster ambition by encouraging the exchange of policy and technical experiences, it brings little fundamental change to the nature of interactions between the signatory Parties and old hurdles to more ambitious national climate change mitigation strategies remain.

The present thesis takes stock of that reality and seeks to build on the available evidence to uncover systematic drivers of and obstacles to climate policy ambition as well as shed light on patterns of (abatement) technology development. This thesis is written with the explicit purpose of informing future policy developments and strengthen the international climate change mitigation regime.

With regard to ambition, this work will explore the dynamics of policy adoption and stringency, with a specific emphasis on carbon pricing policies. In particular, it formulates hypotheses about two groups of factors: (i) the domestic political economy – chapter 2; (ii) the international technological and policy environment – chapter 3. In other words, the former considers the role of local conditions (e.g. regulatory capture, political institutions) whereas the latter argues that the development of new “seemingly" unilateral climate policies can be fostered by a process of policy diffusion, supported by international technological spillovers and changes in (foreign) climate policy choices. The former will draw on political economy theory (Olson, 1965; Stigler, 1971), its application to environmental policy making (Pearce, 2005; Congleton, 1992; Hahn, 1990) and more recent analysis focusing on carbon pricing mechanisms (Jenkins, 2014). The latter will build on the literature on policy diffusion (Simmons and Elkins, 2004; Shipan and Volden, 2008; Volden, Ting, and Carpenter, 2008).

In chapter 2, the focus is specifically on the political economy of carbon pricing. Pricing mechanisms have long been advocated by economists as a cost-effective way to abate GHG emissions, yet they have only recently been adopted more widely, be it at the national or subnational level.[4] This, together with the difficulty of comparing such mechanisms across jurisdictions, means that an analysis of the factors affecting their adoption has so far eluded the empirical researcher. We hold the firm belief, however, that these mechanisms ought to be part of any successful strategy to reduce emissions in line with the objectives of the Paris Agreement and that, therefore, shedding light on these factors is of the essence.

Thus, taking a political economy perspective, this chapter investigates the effect of economic structure and political institutions on the implementation and stringency of carbon pricing policies in a panel of national and North-American sub-national jurisdictions over the period 1990-2015. To that end, an index of carbon pricing stringency is created and calculated. This index, an average (emissions-weighted) carbon price, is the first metric to allow for a consistent comparison of carbon pricing mechanisms across time and space and is, in itself, a contribution to the understanding of such policies. It allows us to show, for instance, that the world average price remains extremely low, at about 1.5USD/tCO2e in 2018. In addition, the analysis in this chapter suggests that (i) political economy factors primarily affected policy implementation and (ii) policy stringency is a highly persistent process.

In chapter 3, we extend the scope of the analysis to non-price climate policies and investigate how changes in a jurisdiction’s external environment might influence its domestic climate change mitigation policy. Specifically, this chapter assumes a non-cooperative approach to climate policy making and identifies three key factors (namely international competitiveness, high cost (and availability) of GHG-abatement technologies, uncertainty about the political and

[4] Experience accumulated over the last 30 years (i.e. since the implementation of the first carbon pricing mechanism in Finland), and especially the recent experience gained when trying to strengthen existing climate change mitigation regimes shows that these can quickly encounter *points of resistance*.

economic implications of mitigation policies) that, until now, have contributed to keep climate change mitigation ambition low. It argues that policy actions by “foreign" jurisdictions might influence domestic climate policy choice via an alteration of the net payoffs of domestic climate policy and an update on the information about the benefits (or costs) of policy adoption. These key dimensions of climate policy making are incorporated in a stylised general equilibrium model of international trade. We then proceed to test our theoretical predictions empirically on a panel of 109 national jurisdictions over the period 1990-2014. The evidence suggests that technology demonstration and learning from past policy experience positively affect (domestic) policy developments.

A corollary of chapter 3 will be that, although the “policy initiative" rests with national or subnational jurisdictions, multilateral frameworks provide an enabling environment for the development and diffusion of climate change mitigation policies. In this respect, for all its potential flaws, the framework created by the UNFCCC and the Paris Agreement might foster the exchange of (i) abatement technologies, (ii) policy experience and ideas, thereby facilitating the implementation of more ambitious domestic emissions abatement targets.[5]

However, for GHG-free technologies to play any role in the reduction of world GHG emissions, said technologies actually have to be developed. Yet, despite entry of new actors, China in particular, the R&D activities leading to the creation of new technologies remain concentrated in a few (groups of) countries. For this reason, innovation activity undertaken by medium or large innovative countries play a prominent role in influencing the technological course of the rest of the world. In particular, sustained innovation in GHG-abating technologies by these countries is needed if we are to succeed in achieving the goal of the Paris Agreement. In our last chapter, chapter 4, we shed light on the innovation activity of one such country, the UK, with regard to electricity supply technologies. Further innovation in electricity supply technologies is a necessary condition to reduce emissions from the power sector and achieve broader decarbonisation of the economy. The analysis builds on and extends Jamasb and Pollitt, 2011; Jamasb and Pollitt, 2015.

This chapter provides both a methodological contribution – providing a strategy for the identification of (GHG-abating) electricity supply technologies using a machine learning search strategy based on patents' title and abstract – and new insights regarding the firm-level patterns of innovation in these technologies based on priority patents filed at the UK Intellectual Property Office over the period 1955-2016. These renewed insights are important in light of the recent history of the Electricity Supply Industry (ESI) of major western economies, which was marked by a transition toward liberalised electricity markets and a policy-led push to decarbonise the electricity generation portfolio. Both of these changes not only affected the pace and nature of innovation activity in the sector but also altered the set of innovative actors.

[5]Indeed, jurisdictions around the world have, at times very effectively, experimented with a range of policies aiming at reducing emissions in a broad range of sectors of their economies. This policy experience is invaluable when it comes to expanding carbon pricing schemes – and other climate policies – to new jurisdictions or strengthening existing ones.

The analysis in this chapter provided us with three main insights. First, the innovation activity shifted away from large (integrated) generation, transmission and distribution utilities to (smaller) equipment manufacturers or R&D firms. Second, the distribution of patent filings over the sample period is heavily skewed, with a small number of actors constituting a large proportion of filings. This is particularly true for OEMs. Third, on a related note, we uncovered the predominant role played by lateral innovation in the development of fossil fuel electricity generation technologies (FF).

The clear inconsistency between the stated objective of global average temperature increase and the existing or pledged climate change mitigation policies provides a strong rationale to strengthen them. This thesis allowed me to develop an improved understanding of the dynamics underpinning policy and technological developments, which would help towards that goal. First, our results stress the importance of the sequence of introduction of the climate policies, suggesting that policies weakening incumbents' political and economic influence might foster subsequent implementation of more stringent policies. Second, given the weakness of most existing carbon pricing schemes, a rationale for the development of climate mitigation strategies with multiple GHG abatement tools continues to exist. Third, mechanisms of policy diffusion at play could prove highly valuable when seeking to introduce carbon-pricing mechanisms in new jurisdictions. Finally, we point at the need to target public support to sustain the stream of GHG-abating electricity supply technologies primarily at new (technological) entrants and encourage within firm resource reallocation to 'green' innovation.

Chapter 2

The Political Economy of Carbon Pricing: a Panel Analysis

The entirety of this chapter, including its appendix and associated data, was published online by Oxford Economic Papers on July 10, 2019; DOI: https://doi.org/10.1093/oep/gpz042

2.1 Introduction

The agreement reached in Paris at the end of 2015 was a diplomatic success. Its environmental benefits are, however, much less clear. If fully implemented, current INDCs submitted to the UNFCCC Secretariat place the world on an emissions path that is incompatible with least-cost 2°C scenarios, the goal stated in the Accord (United Nations/Framework Convention on Climate Change, 2015).[1]

As the Intergovernmental Panel on Climate Change (IPCC) Working Group II 'reasons for concern' make clear, this level bears significant risks for human development and is likely to place unprecedented pressure on already stressed ecosystems (IPCC, 2014). Therefore, supplementary commitments to reduce GHG emissions beyond existing INDCs are needed. This will, in turn, require the setting up of new (or the strengthening of existing) environmental policy tools. Historically, these tools took the form of 'command-and-control' regulations, production quotas and subsidies for electricity from renewable energy sources and, more recently, carbon pricing instruments such as carbon taxes or cap-and-trade systems (Bennear and Stavins, 2007).[2] The focus of this chapter is on the latter category.

While the earliest occurrences of these tools can be traced back to the experiences of Northern European states (Finland - 1990, Sweden - 1991), their development has only gained momentum in the last few years. According to World Bank, 2018, thirty-eight new carbon pricing mechanisms started operations between 2005 and 2018, including the California Cap-and-Trade Program and 7 (sub-national) emissions trading schemes in China. These new schemes

[1]Compared with the emission levels under least-cost 2°C scenarios, aggregate GHG emission levels resulting from the implementation of the Intended Nationally Determined Contributions are expected to be higher by 8.7 (4.5 to 13.3) Gt CO_2 eq (19 per cent, range 9-30 per cent) in 2025 and by 15.2 (10.1 to 21.1) Gt CO_2 eq (36 per cent, range 24-60 per cent) in 2030 (United Nations/Framework Convention on Climate Change, 2016).

[2]*Carbon* per se is not a greenhouse gas but carbon dioxide (CO_2) is. We refer to instruments putting a price on CO_2 emissions as carbon pricing instruments.

added to a group of existing carbon pricing tools such as the European Union Emissions Trading System or a range of taxes explicitly based on the carbon content of fossil fuels.

Yet, the introduction of such tools is often faced with strong political economy constraints (Jenkins, 2014) that influence their design and prevent their full (i.e. socially optimal) implementation (Del Rio and Labandeira, 2009). Their influence on the implementation of carbon pricing policies is nonetheless currently under-researched. While substantial attention has been paid to the political economy of energy or renewable energy support (RES) policies, a relatively narrow set of studies have specifically focused on policies making use of carbon pricing mechanisms, be it in a specific national or subnational context, or in an international panel of countries. Furthermore, such studies often focus on policy outcomes as proxies for policy developments but do not directly study the policy tool itself (see, e.g. Gassebner, Lamla, and Sturm, 2011 or Cadoret and Padovano, 2016).

Our study is a contribution to filling this gap. It aims at shedding light on the nature and working of political economy constraints on the development of carbon pricing policies. This allows us to address two fundamental questions pertaining to the design of climate mitigation strategies in the presence of such constraints. How should we adapt the policy design to a specific institutional and economic context? Do political economy constraints constitute a robust rationale in favour of a policy mix as opposed to a single instrument?

The chapter is organised as follows. Section 2.2 reviews the relevant strands of the literature. Section 2.3 briefly discusses carbon pricing (in theory and practice). Section 2.4 introduces the Emissions-weighted Carbon Price and presents the hypotheses while section 2.5 presents the data and discusses the empirical methodology used in the analysis. Section 2.6 discusses the results and section 2.7 concludes.

2.2 Literature review

More often than not, economic policies resulting from the legislative and political bargaining process constitute sub-optimal social outcomes. Political economy theory provides a useful analytical framework to rationalize them. Olson, 1965 highlights the role played by groups with shared interests in shaping policy outcomes and the factors that drive their behaviour. Building on Olson's conjecture, Stigler, 1971 proposed the idea of regulatory capture, which views the State as a provider of regulation and the industry as an active seeker of regulation designed and operated for its own benefit.

The relevance of these theoretical insights has long been discussed in the context of environmental policy making (Pearce, 2005). Congleton, 1992 takes an institutional perspective to the issue; proposing that political institutions, rather than resource endowments, determine a country's environmental regulation. More precisely, he argues that due to their focus on longer term outcomes, democratic institutions tend to deliver more stringent environmental regulations.[3] At the same time, democratic systems allow a plurality of, sometimes divergent, interests to be voiced. Hahn, 1990 attempted to identify rationales for the emergence of incentive-based mechanisms and suggested that environmental policy is the result of a 'struggle' between different interest groups.

In the context of carbon pricing, the introduction of (economy-wide) schemes may induce profound changes in the magnitude and distribution of welfare. Therefore, even if the welfare of the polity as a whole is greater in an economic system constrained by environmental policies, one may expect strong opposition on the part of both consumers and producers. On the consumption side, some studies have shown that the willingness to pay for carbon emissions is low (Jenkins, 2014). Moreover, carbon pricing schemes have been found to be regressive, with varying degrees, in a wide range of institutional contexts (Wier et al., 2005; Grainger and Kolstad, 2010), with only some of them designed to alleviate this effect (Bowen, 2015). On the production side, sectors with assets whose value would be severely diminished in case of carbon pricing are expected to strongly oppose policy change; a possibility that Joskow and Schmalensee, 1998 discuss in the case of the U.S. SO_2 market. It is therefore unsurprising that the introduction of carbon pricing policies proved highly contentious in virtually all jurisdictions where they have been considered.

In addition, carbon pricing policies have at times lacked bi-partisan/multi-party support and been the source of deep partisan divides. Australia, where the policy debate has been characterised by high political polarisation (O'Gorman and Jotzo, 2014) and the road to its implementation has been "long and bruising" (Jotzo, 2012), provides a salient case in point. The policy was implemented by a minority Labour government and was repealed as soon as Conservatives returned to power after an election where one of the key issues was precisely the carbon pricing policy. This suggests that carbon pricing policies can only be politically sustained if they benefit from strong bi-partisan support.

Lastly, insights drawn from analyses of the liberalisation of energy markets are also relevant to our investigation. Pollitt, 2012 takes stock of the energy market liberalisation processes to draw lessons about the role of policy in energy transitions and argues that liberalisation *per se* will have little impact on the shift toward a low carbon energy mix. Rather, the willingness of societies to bear the cost of environmental policies will. Hence, liberalisation is not necessarily *neutral* for carbon pricing policy formulation as it has made the cost of those policies increasingly apparent to consumers (Pollitt, 2012). Evidence from the U.S. (Jenkins, 2014) suggests that citizens are indeed quite sensitive to the direct costs induced by carbon pricing policies, even if the net cost is brought (close) to zero via tax rebates or other fiscal mechanisms.

Our analysis seeks to uncover systematic patterns in the relationship between some of the factors highlighted above and carbon pricing policy adoption in a panel of jurisdictions. Some analyses taking advantage of the availability of panel data have shed light on political economy dynamics of similar policies. Marques, Fuinhas, and Pires Manso, 2010 analyse the drivers of

[3] This argument runs against the standard view that political representatives are self-interested and focused on short-term electoral cycles.

the deployment of renewable energy in European countries. Using fixed effects (panel data) regression and vector decomposition, they find evidence that the conventional energy sector lobby and the level of CO_2 emissions impede the deployment of renewable energy sources for electricity production. Chang and Berdiev, 2011 focus on the electricity and gas industries and seek to disentangle the effects of government ideology, political factors and globalisation on energy regulation in 23 OECD countries over the period 1975-2007. They conclude that left-wing governments promote regulation in gas and electricity sectors and that less fragmented governments contribute to deregulation of gas and electricity industries. Beers and Strand, 2015, analysing data from 200 countries for the political determinants of fossil fuel pricing during the period 1991-2010, found that higher GDP levels lead to higher fuel prices (higher taxes or lower subsidy rates) and that a presidential system (unlike parliamentarian or proportional representation systems) could lead to significantly lower gasoline and diesel prices.

However substantial the discussion of political economy factors in environmental policy formulation has been, relatively less attention has been paid to the political feasibility of carbon pricing policies and, equivalently, to the variables that influence their implementation and strength. To our knowledge, only Del Rio and Labandeira, 2009, Gawel, Strunz, and Lehmann, 2014 and Jenkins, 2014 bring the issue to the fore. Shedding further empirical light on these dynamics is particularly important as we believe that they may differ in nature or in strength from those of: (i) excise duties, which in most occurrences constitute an indirect way to tax road transport; (ii) other climate policies, whose cost is less visible to the final consumer. In the absence of more refined assessment, suggestions about a way forward for the implementation of carbon pricing when faced with *political economy* constraints are, at best, incomplete. Before turning to that analysis we briefly review the rationale and tools for a carbon price.

2.3 Carbon pricing policies: theory and practice

In theory, provided that the public authority can credibly commit to a state-contingent carbon price path and in the absence of transaction costs, the carbon price signal should be economy-wide (Tirole, 2012).[4] Indeed, the externality associated with the release of GHG into the atmosphere is the same regardless of its source (i.e. sector of origin) or type of use. Any departure from this situation will inevitably introduce distortions between sectors and/or types of user.

Two market-based mechanisms (and hybrid combinations[5]) have emerged: carbon taxes and Emissions Trading Schemes. The former places a set price on each unit of CO_2 emitted into the atmosphere, leaving an uncertainty about the resulting level of emissions; the latter sets an emissions cap and leaves to the market the creation of the price signal. Even though both mechanisms share the same underlying motivation and, under complete knowledge and

[4] If transaction costs (i.e. costs of monitoring and verification) are positive, then optimal coverage may not be 100%. Additional emissions should then only be included if the marginal benefit in terms of enhanced cost efficiency outweighs the marginal cost of monitoring and verifying emissions.

[5] Hybrid schemes combine elements of price and quantity schemes by, e.g. setting floors and caps on the prices delivered by quantity schemes (Roberts and Spence, 1976; Weitzman, 1978).

perfect certainty, are theoretically equivalent and deliver the same environmental outcome, they relate to two slightly different views about carbon pricing.[6] The first view emphasizes the use of carbon pricing mechanisms to internalize the externality associated with GHG emissions and hence is more sympathetic to carbon taxes. In that case, the price of carbon should closely track the Social Cost of Carbon (SCC). The second stresses the achievement of a set carbon budget over a given planning horizon in a cost-effective way, in which case the price will follow the dynamically cost-effective price path (Rubin, 1996).

Importantly for us, these schemes differ also in their practical implementations. On the one hand, most carbon taxes are based on the carbon content of fossil fuels. On the other hand, an Emissions Trading Scheme is based on actual verified emissions at covered (stationary) plants.[7] Therefore, an ETS can in theory include fugitive and industrial processes emissions in addition to emissions from fuel combustion.

In 2015, the last year of our panel(s), 35 national and 21 subnational jurisdictions had an operating Emissions Trading Scheme while 15 national and 1 subnational jurisdictions had a carbon tax targeting at least one type of fossil fuel (i.e. coal, oil or natural gas). Among jurisdictions operating an ETS at the time, 47 covered industry and 54 covered the power sector while the same sectors were included in 14 and 12 carbon tax schemes, respectively. Table 2.1 provides a summary of sectoral coverage per type of pricing mechanism.

TABLE 2.1: Sectoral coverage (2015) – number of jurisdictions

	Carbon tax schemes (total: 16)	ETSs (total: 57)
Industry	14	47
Power	12	54
(Road) Transport	12	5
Aviation (domestic)	4	31
Buildings (residential and commercial)	12	8
Agriculture or Forestry	11	2
Waste	12	1

Note: The figures presented in this table count each jurisdiction participating in the EU-ETS as a separate scheme. A description of the sectoral nomenclature is available in appendix B and a complete list of the jurisdictions operating a carbon pricing mechanism as of 2018 is available in appendix A.4.
Source: World Bank, 2018

2.4 Carbon pricing and its drivers

Following on the above discussion, we argue that introducing a carbon pricing mechanism involves two decisions. First, a decision on whether or not to enact a pricing scheme, regardless

[6]Outcomes may differ when there is uncertainty about either the marginal cost or benefit of abatement and the relative superiority of one instrument over the other depends on the relative slopes of the marginal abatement and cost curves around the optimum (Weitzman, 1974). Weitzman's original article considers only a static one-period model and so is more relevant to flow rather than stock pollutants like CO_2 but his conclusions were supported in theoretical settings closer to that of stock pollutants (Pizer, 2002; Hoel and Karp, 2002).

[7]Emissions from the aviation sector, which have recently been included in some ETSs, are estimated based on the fuel consumption of each aircraft, multiplied by the appropriate emissions factor (European Commission, 2012).

of the price level or the coverage. Second, a decision about the appropriate – or politically feasible – stringency (i.e. average price). The implementation of a carbon pricing policy is recorded by a dummy variable taking value 1 if it is in force in a given country-year, 0 otherwise. The stringency is captured by the average (emissions-weighted) carbon price and is described in section 2.4.1. The hypotheses formulated about the drivers of implementation and stringency are presented in section 2.4.2.

2.4.1 Carbon price and coverage: an Emissions-weighted Carbon Price

Following 'first-best' theoretical prescriptions, applied macroeconomic integrated assessment models often assume a single, economy-wide (100% coverage) carbon price. Yet, experience with carbon pricing policies suggests that their implementation has rarely, if at all, followed such prescriptions. First, most of the schemes under consideration entailed low coverage at time of introduction – due to, e.g., sectoral or fuel-based exemptions, or a combination of the two – and their coverage remained partial over their lifetime. Therefore, the price tag alone cannot appropriately reflect the stringency of a carbon pricing scheme. It has to be analysed together with its coverage. Second, careful observation of policy developments shows little consistency between the stated environmental goals (and implied GHG budgets) and implemented carbon prices and, as will be shown in section 2.4.1.2, the carbon price is usually not unique within jurisdictions, let alone across them.

In order to accurately account for these two dimensions of carbon pricing mechanisms and reflect their stringency, we introduce the concept of an Emissions-weighted Carbon Price (ECP).[8] This price, computed on a yearly basis, is a weighted average of all carbon price signals present in an economy at a point in time where the weights are the quantity of emissions covered as a share of that jurisdiction's total GHG emissions. To our knowledge, this is the first attempt at capturing the economy-wide stringency of carbon pricing policies in a consistent and standardised way.[9] Before turning to a discussion of the underlying methodology, we review its two components: coverage and price.

2.4.1.1 Coverage

The coverage of carbon pricing schemes is usually defined at the sectoral level although carbon taxes can be defined per fuel type too. The main difference between emissions trading schemes and carbon taxes lies in that the former sometimes cover multiple gases whereas the

[8] The methodology behind the computation of the Emissions-weighted Carbon Price is similar to that suggested for the Effective Carbon Rate (OECD, 2015). However, the OECD methodology accounts for both explicit carbon prices and energy duties that indirectly price carbon, which we believe is misleading since, as we have emphasized and as the OECD itself acknowledges (OECD, 2015), the motivations behind their introduction are often unrelated to climate change concerns.

[9] Measuring policy stringency is inherently difficult, even more so when the metric needs to be comparable across jurisdictions. Most studies rely on indirect measures of policy stringency such as private-sector cost measures, measures based on pollutant emissions and environmental policy enforcement expenditures (Brunel and Levinson, 2013). The OECD calculates an aggregated index of policy stringency at the country level based on information primarily related to climate and air pollution (Botta and Kozluk, 2014).

latter only apply to the carbon content of fossil fuels and, by extension, to CO_2 emissions. The present chapter focuses exclusively on CO_2. Provided that accurate measurement of sectoral CO_2 emissions is available, sectoral coverage of a scheme can easily be translated into 'covered' CO_2 emissions as a share of total, CO_2 equivalent, GHG emissions. Based on this information, coverage figures were calculated for 135 national and 63 subnational (50 US States and 13 Canadian Provinces and Territories) jurisdictions as well as a hypothetical 'World' jurisdiction between 1990 and 2015.[10] Figure 2.1 provides an overview of the coverage of carbon pricing mechanisms in selected jurisdictions.[11] Panel (a) clearly shows that there is significant variation in coverage of carbon tax schemes across jurisdictions. Between 1992 and 2005, Denmark's scheme covered roughly 70% of its GHG emissions, the highest share among all jurisdictions considered, while Finland's coverage was only 30%. It is also striking to see that if those schemes imply a significant coverage in terms of respective national emissions, they mean very little in terms of world GHG emissions, as illustrated by the 'World' coverage. Except for the 'structural break' observed in 2005 for some countries, which reflects the fact that they adapted their legislation to avoid an overlap with the EU-ETS, coverage of GHG emissions by tax schemes is, for each country individually, relatively stable over time. Similarly, the coverage induced by the ETS in the selected countries does not show significant variation over time. Yet, one notes that all countries that are part of the EU-ETS exhibit different coverage figures, despite the ETS being harmonized across all countries. A potential explanation for these cross-country differences is that they reflect the differences in economic structure across participating countries.

In addition to the jurisdictions presented in Figure 2.1 several others have introduced carbon pricing policies. Switzerland introduced a carbon tax in 2008 covering about 28% of its total emissions. The coverage remained relatively stable over time, with the scheme covering 27% of emissions in 2012. In that same year, Japan introduced a carbon tax covering 69% of its emissions. Other jurisdictions opted for ETSs. This is the case of New Zealand, which introduced its scheme in 2010 with a coverage of 43% (gradually increased to 54% following inclusion of waste treatment activities in the scheme).

At the subnational level, another group of jurisdictions can be identified: US States participating in the Regional Greenhouse Gases Initiative (RGGI). This scheme is a regional initiative gathering initially 10 (but now 9: the state of New Jersey pulled out of the scheme in 2012) North-Eastern US States. Figure 2.2 shows the implied coverage of the scheme in the 10 participating states over the period 2009 (start year)-2012. It is again striking to see that substantial cross-state variation characterizes coverage. New Hampshire exhibits the highest coverage

[10] See appendix A for a description of the methodology. At the national level, although our initial intention was to cover all jurisdictions, the cross-section dimension of our panel has been constrained by IEA emissions data availability while the time dimension has been constrained by CAIT data availability. At the subnational level, our focus on North America is driven by the fact that, up to 2015, that region concentrated most of the subnational carbon pricing schemes and that we were unable to gather robust data on the Chinese ETS pilot schemes or the Tokyo, Saitama, and Kyoto schemes.

[11] Besides the 'World' jurisdiction, the jurisdictions for which information is presented in Figures 2.1 to 2.4 are among the earliest adopters of carbon pricing mechanisms – exclusive of the EU-ETS countries – and for which the information is therefore available for a meaningful number of years.

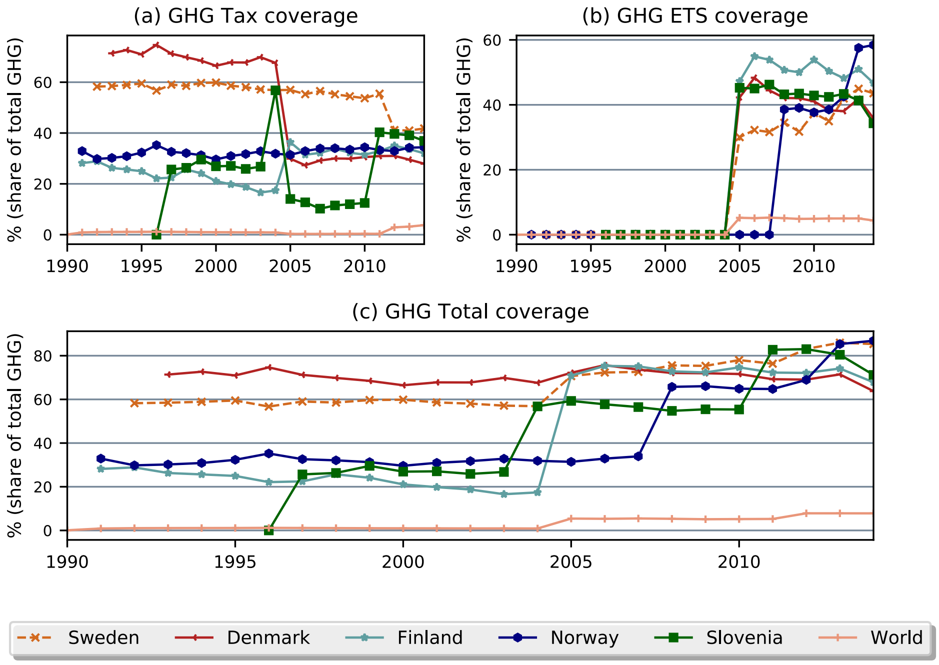


FIGURE 2.1: Carbon pricing coverage – selected (national) jurisdictions

over the entire period, oscillating between 36.41% in 2009 and 34.42% in 2014. The coverage in all other participating states is between 13.19% (New Jersey - 2009) and 34.42% (New Hampshire - 2012). Outside the RGGI initiative, British Columbia launched its own carbon tax scheme in 2008, covering roughly 70% of its total GHG emissions while, in 2013, California introduced a Cap-and-Trade (CaT) mechanism covering approximately 32% of its emissions.[12]

2.4.1.2 Price

Coverage is only one side of the coin. The other is the price level. Countries that have introduced carbon pricing policies have experimented with different strengths of the price signal, which varies mainly along three dimensions: time, jurisdiction, and sector(-fuel). In other words, the price signal varies both across and within countries, introducing distortions between countries as well as between sectors of a given country. Importantly, however, distortions introduced by Emissions Trading Schemes are only between covered and non-covered sectors (since the price signal is the same across all covered sectors and fuels) whereas a carbon tax scheme also introduces distortions at the sector-fuel level.

Figure 2.3 displays the total (i.e. the sum of the tax rate and the ETS allowance price, as applicable) price of CO_2 (in 2015 \$US/tCO_2e) in selected sectors of selected countries for coal.[13] The carbon price does not vary much across fuels, suggesting that most tax schemes apply the same tax rate to all fossil fuels. The most significant variations arise across countries and, hence,

[12] As of January 1st, 2015, new activities were added to the California CaT, increasing coverage to about 85% of California's total GHG emissions.
[13] Figures A.1.1 and A.1.2, available in appendix A, show the total price for oil and natural gas, respectively.

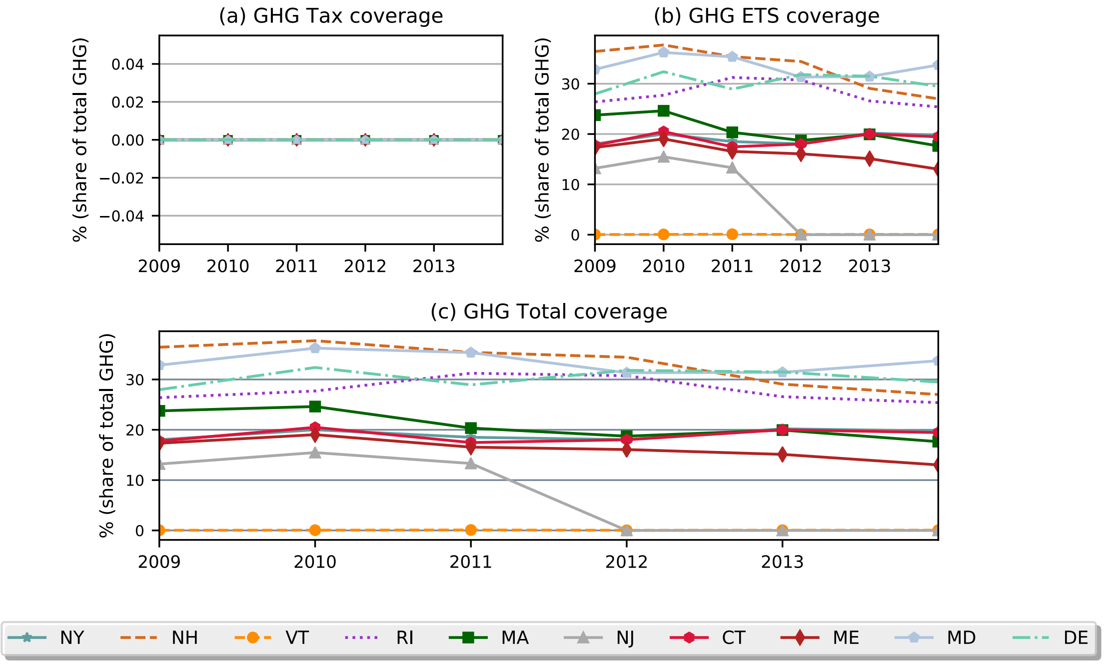


FIGURE 2.2: Carbon pricing coverage – US Regional Greenhouse Gas Initiative

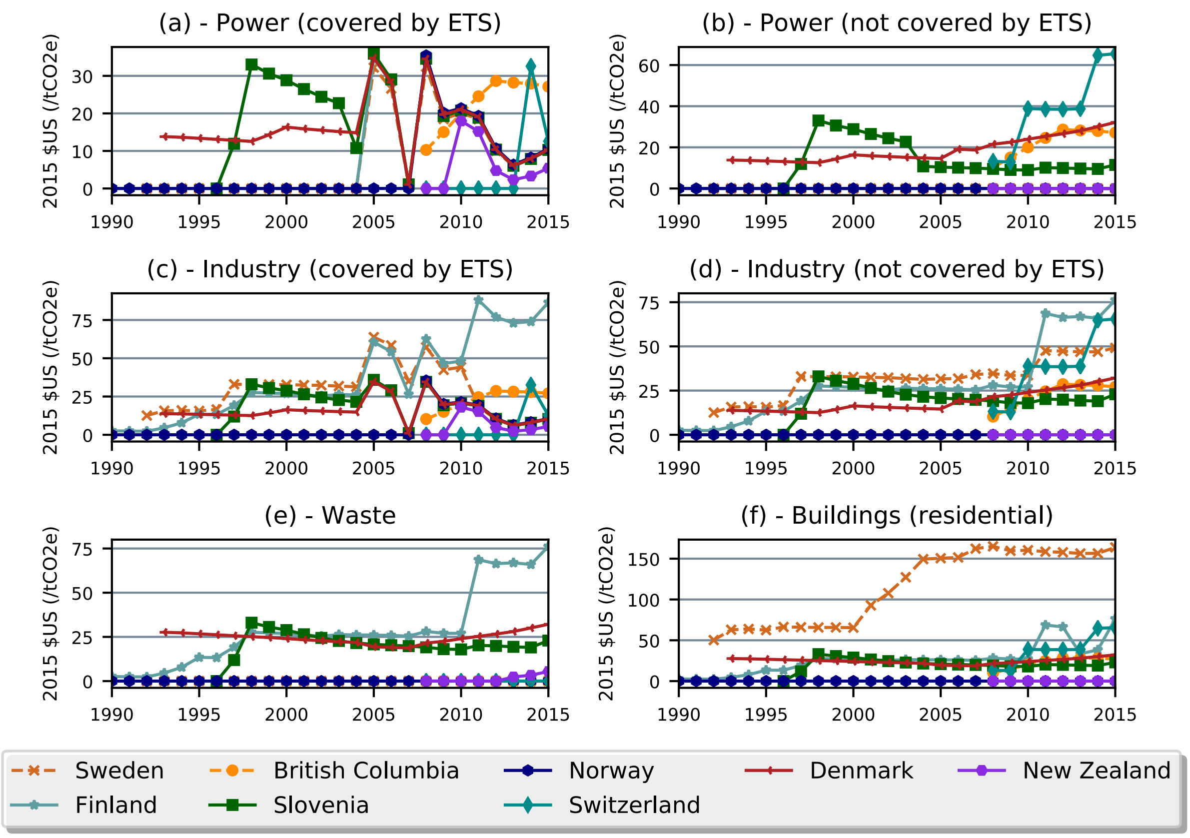


FIGURE 2.3: Total carbon price over time – coal/peat

across sectors within those countries. A look at panel (b) of Figure 2.3 shows that, among the selected countries, the power sector in Sweden is confronted to the highest price signal whereas the sectors in the other countries face much lower carbon prices.

2.4.1.3 The Emissions-weighted Carbon Price (ECP)

Combining sector- or sector-fuel-level coverage and price information allows for the calculation of an economy-wide Emissions-weighted Carbon Price (ECP). To compute the ECP each emitted tonne of GHGs is attributed the corresponding total price signal. That is, emissions covered by either a tax or an ETS receive the associated tax rate or permit price as price tag whereas emissions of a sector covered by both schemes receive the sum of the tax rate and the permit price.[14]

The evolution of the ECP in selected countries over the period 1990-2015 is presented in Figure 2.4. One observes that among all selected countries, only Sweden's ECP has increased steadily over time. All other countries exhibit either constant (e.g. Norway) or decreasing (e.g. Denmark) ECPs. Moreover, contrary to what is generally understood, the ECP varies across countries that are part of the EU-ETS. This is partly due to the presence of carbon taxes in some – but not all – countries, which create an additional price signal for some emissions. It is also, perhaps more importantly, due to differences in the relative size of sectors and their respective CO_2 intensity, as mentioned in section 2.4.1.1. This feature is particularly well illustrated by the ECP of states participating in the US RGGI (Figure 2.5).

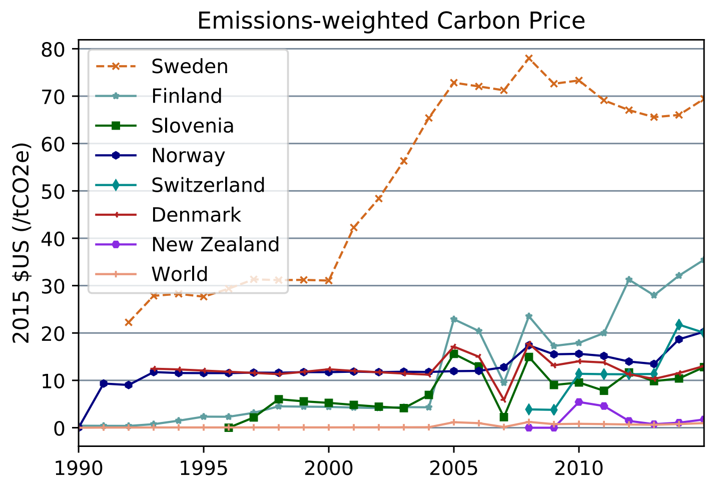


FIGURE 2.4: ECP – selected (national) jurisdictions

Lastly, note that some countries' ECP exhibit more variability than others. For this specific group of countries, this is due to the relative importance of emissions covered by the EU-ETS as opposed to those covered by the respective national carbon taxes. Indeed, the (futures) price of EUAs, i.e. EU-ETS emissions allowances, exhibited strong variability over the sample period.

[14] Note that the ECP can be computed using time-varying or fixed weights. In the former case, weights (i.e. sector-fuel emissions share) are the year-specific emissions share; in the latter, we use 2013 emissions share. The latter is used in the empirical analysis as it is not subject to changes in emissions shares (i.e. weights) that might have been the result of the policy itself. See appendix A.3 for a formal presentation.

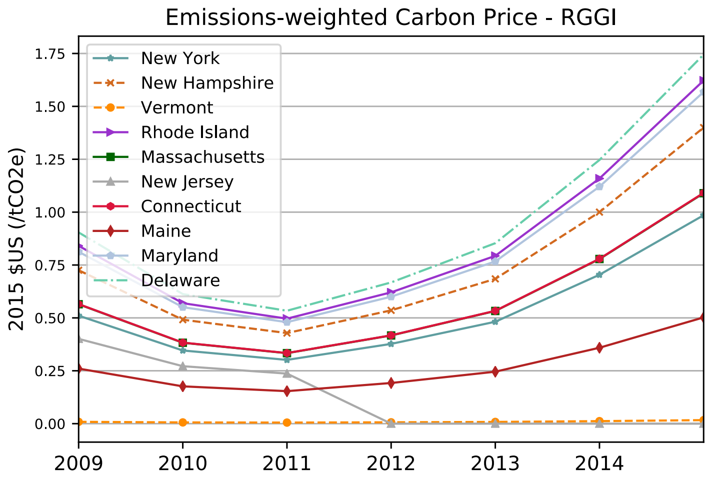


FIGURE 2.5: ECP – US Regional Greenhouse Gas Initiative

2.4.2 Hypotheses

We now formulate hypotheses about the determinants of policy implementation and stringency. These are grouped as follows: (i) regulatory capture; (ii) political institutions; and (iii) macroeconomic determinants. A summary is presented in Table 2.2.

2.4.2.1 Regulatory capture

Power sector Any form of carbon pricing that includes the power sector might impose costs (e.g. reduced profits or capital losses) on those electricity producers that produce electricity from fossil fuels. We expect these costs to be higher the larger the share of electricity produced from fossil-fuelled power plants which, following Olson, 1965, would weaken the political feasibility of carbon pricing regulation. This argument needs to be nuanced, however. First, the extent to which carbon pricing policies affect the value of covered firms depends on their capacity to *pass* the additional cost *through* to consumers. In aggregate, under perfect competition and 100% pass through, electricity producing firms' profits will remain largely unaffected.[15] With less than 100% pass through the change in equilibrium market price will not entirely reflect the increase in cost and firms' profit will be affected. Second, one does not necessarily expect the electricity generating sector to react in the same way to a carbon tax and a cap-and-trade system. In the case of the former, the sector will, at best, remain unaffected whereas in the case of an ETS, the possibility of capturing significant 'windfall profits' exists if emissions permits are freely allocated. Such a possibility has probably played a significant role in dampening the opposition of affected sectors to the introduction of such schemes. Several studies have examined that possibility and the associated rent-seeking behaviour both theoretically (Rode,

[15] There is still, however, the possibility that the profits of coal fired power plants will fall relative to gas and non-fossil generators. Hence carbon pricing policies will affect individual firms differently depending on the composition of their generation portfolio.

2013) and empirically (Markussen and Svendsen, 2005). The empirical evidence suggests that powerful (and CO_2-intensive) sectors were successful in influencing the design of GHG trading systems. In fact, except for the US RGGI, all emissions trading schemes have been introduced with close to 100% free allocation of emission permits (World Bank, 2014). It is difficult to explicitly account for such effects in an econometric investigation but we note at this stage that it is likely to reduce the magnitude of the coefficients on the variables accounting for the role of CO_2-intensive sectors, including the power sector.

Industry Besides the power sector, other energy-intensive sectors, broadly defined as 'industry' are likely to oppose a carbon pricing scheme on the grounds that it holds the potential to increase production costs. There are two channels via which costs to industry could be pushed upward by a carbon pricing policy. A direct channel whereby CO_2-intensive industries that fall within the scope of a carbon pricing scheme will have to pay for their own CO_2 emissions; and an indirect channel whereby the introduction of carbon pricing policies covering the electricity generating sector leads to an increase in wholesale (and retail) electricity prices (as has been observed after the introduction of the EU-ETS (Sijm et al., 2008)) which, in turn, might raise the production cost of electricity-intensive industries. This argument closely follows Cadoret and Padovano, 2016.

International competitiveness As emphasized by Aldy and Pizer, 2012, sectors of the economy that are export-oriented should be more resistant to the introduction of a carbon price as it risks putting them at a competitive disadvantage in international markets. Care is usually taken to design the schemes in ways that minimize the international competitive disadvantage that domestic firms may suffer from but jurisdictions that are very exposed to international markets may nonetheless be less inclined to implement carbon pricing policies.

2.4.2.2 Political institutions

Political regime Congleton, 1992 argues that autocrats' time horizon is shorter than that of democratic planners and they therefore set weaker environmental targets. Yet, Hahn, 1990 also argues that liberal democracies offer the possibility for different interest groups to express their views and 'weigh' on the legislative process, in which case regulatory outcomes will be a balancing act that reflects the relative bargaining power of the different interest groups. This could work both in favour or against the introduction of carbon pricing policies, depending on interest groups' relative lobbying strengths.

Government ideology Prior studies have found left wing governments implement more stringent environmental policies (Chang and Berdiev, 2011; Cadoret and Padovano, 2016). Fankhauser, Gennaioli, and Collins, 2015, however, found the political orientation of the government to be irrelevant to the number of climate laws passed in their sample of jurisdictions. We test whether the orientation of the executive branch of government with regard to economic policy affects the implementation and/or stringency of carbon pricing schemes.

Institutional capacity A relatively high degree of institutional capacity is a prerequisite for the introduction of any form of regulation and, a fortiori, to introduce a carbon pricing scheme. We expect institutional capacity to be positively correlated with the presence of a carbon pricing scheme but not necessarily with the level of the ECP. Indeed, the 'institutional burden' arises from the creation of such a scheme, irrespective of the level of the price associated with it.

International dynamics Membership of international organisations (such as the OECD or the EU) or international institutional frameworks (such as the Annex-I countries of the Kyoto Protocol) plays a significant role in the presence and development of carbon pricing policies. For example, the EU, a club of countries cooperating on a wide range of issues – including the environment, has implemented an EU-wide emissions trading system. Several EU Member countries currently part of the system were 'dragged in' and implemented it only because it was part of the preexisting legislative *acquis* (Robinson and Stavins, 2015). This is the case, for instance, of current EU Member States that joined the Union in 2004, i.e. a year before the start of the EU-ETS but a few months after Directive 2003/87/EC, which implemented the EU-ETS, was passed. Having committed to a reduction of their GHG emissions, these countries may have had an additional incentive to develop climate mitigation strategies, including carbon pricing policies.

2.4.2.3 Macro(economic) determinants of environmental policy

Finally, besides the sector-specific stance towards carbon pricing and the political institutions of a jurisdiction, we note two further factors potentially affecting implementation and stringency of a carbon pricing scheme. First, under the assumption that environmental quality is a normal good, the willingness to pay for CO_2 emissions abatement rises with income. Therefore, we expect the income level (per capita) to be positively associated with the probability of implementation of a carbon pricing policy as well as the Emissions-weighted Carbon Price. Second, given the direct economic cost that pricing carbon entails, larger emitters (per capita) may be less prone to introduce pricing policies.

2.5 Data and identification strategy

2.5.1 The dataset

The analysis is performed on three different panels: 124 national jurisdictions – panel A, 50 US States – panel B – and 13 Canadian Provinces – panel C.[16] Panel A runs over the period

[16] Although the ECP is calculated for 135 national jurisdictions, data availability for some of our covariates constrains the panel dimension of our sample to 124 – models (I) and (III) – and 110 units – models (II) and (IV). For

TABLE 2.2: Summary of hypotheses

Category	Variable	Expected sign Carbon Price (Y/N)	Expected sign Carbon Price (Level)
Regulatory capture	Power-coal	-	-
	Power-oil	-/0	-/0
	Power-gas	-/0	-/0
	Industry	-	-/n.a.
	International competitiveness	+/-	+/-
Political institutions	EU	+	+
	Annex-I	+	+
	Institutional capacity	+	n.a.
	Level of democracy	+	n.a.
	Left	+	+
Macro determinants	GDP per capita (WTP)	+	+
	CO_2 emissions per capita	-	-

1990-2015; panel B starts in 2008 and ends in 2015; panel C covers the years 2005-2015. This represents (a maximum of) 3224 country-year observations, 400 (US)State-year observations and 143 (Canadian) Province-year observations. The actual emissions-weighted carbon price is only observed for those jurisdictions that have selected into a pricing mechanism (either ETS or tax, or both). In 2015, 35 national jurisdictions, 11 US States and 2 Canadian Provinces had had a carbon pricing mechanism in force in at least one year. That is, the ECP is observed for 420 country-year, 70 (US)State-year and 11 (Canadian) Province-year pairs. This particular structure of the data has implications for our empirical analysis – see section 2.5.3.

2.5.2 Covariates

This section introduces the variables used to investigate the hypotheses presented in section 2.4.2. The corresponding summary statistics are presented in Table 2.3.

Regulatory capture Previous literature has proxied the strength of the lobbying exercized by the power/energy sector in at least two ways. First, Fredriksson, Vollebergh, and Dijkgraaf, 2004 and Fredriksson and Vollebergh, 2009 use the share of value added of the energy industry in total GDP. Second, Marques, Fuinhas, and Pires Manso, 2010 and Marques and Fuinhas, 2011 disentangled the specific role played by different fossil fuel sources using the contribution of each of them to total electricity production. Since coal, gas and oil electricity generation would not be similarly affected by the introduction of a carbon pricing scheme, we follow this last approach and use their share in total electricity generation as proxies for their influence on policy developments. To capture the lobbying activity of CO_2/energy-intensive industries, we follow Cadoret and Padovano, 2016 and use the value added of industry (as a share of GDP). Finally, the effect of trade openness is captured by the sum of a jurisdiction's exports and imports (as a share of GDP).

panel A, each estimator is therefore presented for two alternative specifications because the *Left* variable is not available for all panel units. In addition, panel A is unbalanced.

Political institutions We introduce an institutional capacity indicator, constructed as the simple average of the World Bank's 'Government Effectiveness' and 'Regulatory Quality' indicators World Bank, 2016b. This follows Steves, Treisman, and Teytelboym, 2011.[17] The first year of these series is 1997 but they only became available on an annual basis in 2002. Therefore, years 1998 and 2000 are filled using a linear interpolation method. Our main proxy for the state of democracy (*Dem*) comes from the Center for Systemic Peace, Polity IV project, 2015. As a robustness check, we also perform the analysis with two variables taken from the Varieties of Democracy Database. The first (*Polyarchy*) measures to what extent the ideal of electoral democracy is achieved whereas the second (*Libdem*) measures performance regarding the achievement of principles of liberal democracy Varieties of Democracy, 2018.[18]

To investigate the effect of the political orientation of the executive with respect to economic policy in national jurisdictions we create, based on Cruz et al. (2018) in Varieties of Democracy, 2018, a variable (*Left*) which takes value 1 whenever the ruling party is identified as left wing party and 0 otherwise. The '0' therefore lumps together right-wing and centre parties as well as parties whose political platform does not take a clear stance regarding economic policy. For panel B, the variable used (*Ideology*) captures the median ideology in the state's house of representatives, as defined in Shor and McCarty, 2011. No such variable is available for subnational Canadian jurisdictions. Finally, the effect of EU membership (*EU*) is tested with the use of a dummy variable that takes value 1 whenever a country is a member of the EU, and 0 otherwise.[19]

Macro determinants To control for general economic and environmental conditions, we use GDP (PPP, $US 2011) and CO_2 emissions (metric tonnes), both per capita.

2.5.3 Model and identification strategy

Our objective is to identify some of the determinants of carbon pricing policy implementation as well as stringency. To that end we introduce two (sets of) models. One that relates our covariates to a binary outcome variable recording the presence of a carbon pricing scheme for a given jurisdiction-year entry, another relating some of these same covariates to the stringency of the scheme. A general representation of each of them is

$$\mathbb{1}_{it} = \alpha + \boldsymbol{\psi}'\boldsymbol{X_{it}} + \boldsymbol{\gamma}'\boldsymbol{Z_{it}} + \boldsymbol{\eta}'\boldsymbol{W_{it}} + d_t + u_{it} \tag{2.1}$$

$$ECP_{it} = \eta + \delta ECP_{i,t-1} + \boldsymbol{\psi}'\boldsymbol{X_{it}} + \boldsymbol{\gamma}'\boldsymbol{Z_{it}} + \boldsymbol{\eta}'\boldsymbol{W_{it}} + d_t + \phi_i + \epsilon_{it} \tag{2.2}$$

where $\mathbb{1}_{it}$ is an indicator variable capturing the operation of a carbon pricing scheme, ECP_{it} is the Emissions-weighted Carbon Price, $\boldsymbol{X_{it}}$ is the vector of regulatory capture variables, $\boldsymbol{Z_{it}}$

[17] Correlation with the World Bank *Control of Corruption* estimate is also investigated, see section 2.6.3.

[18] Such variables are not available for subnational jurisdictions but their inclusion would most likely add little to the model as there would be little cross-section and/or time variability.

[19] Earlier work tested the role of being listed in Annex-I and Annex-II of the Kyoto Protocol. Both institutional features turned out to have negligible impact on our outcome variables.

TABLE 2.3: Variables' sources and summary statistics

Variable	Jurisdiction	Source	Mean	Std. Dev.	Min.	Max.	N
Pricing	National	Author (see appendix)	0.12	0.33	0	1	3510
	US States	Author (see appendix)	0.17	0.37	0	1	400
	Can. Prov./Terr.	Author (see appendix)	0.12	0.32	0	1	143
ECP†	National	Author (see appendix)	12.84	16.67	0.002	95.21	420
(time-invariant weights)	US States	Author (see appendix)	0.88	1.38	0.01	9.66	70
	Can. Prov./Terr.	Author (see appendix)	16.24	10.18	2.19	29.48	11
Elec. generation-coal,	National	World Bank, 2016a	16.78	25.87	0	100	3477
% of total	US States	U.S. EIA, 2015	39.61	28.87	0	97.79	400
	Can. Prov./Terr.	Statistics Canada, 2016a	15.88	24.77	0	69.93	143
Elec. generation-gas,	National	World Bank, 2016a	22.63	30.12	0	100	3477
% of total	US States	U.S. EIA, 2015	24.5	23.48	0	98.51	400
	Can. Prov./Terr.	Statistics Canada, 2016a	6.82	9.52	0	38.37	143
Elec. generation-oil,	National	World Bank, 2016a	19	27.96	0	100	3477
% of total	US States	U.S. EIA, 2015	2.28	10.24	0	76.21	400
	Can. Prov./Terr.	Statistics Canada, 2016a	3.25	7.46	0	34.65	143
Industry VA,	National	UN data	32.11	11.67	6.3	84.55	3452
% of GDP	US States	US BEA, 2016	21.5	7.25	0	46.5	400
	Can. Prov./Terr.	Statistics Canada, 2016b	29.83	11.26	15.37	58.56	143
EU	National	Author-created	0.15	0.35	0	1	3510
Institutional capacity	National	World Bank, 2016b	0.1	0.98	-2.19	2.26	2538
Democracy	National	Polity IV project	3.7	6.74	-10	10	3247
Left	National	Varieties of Democracy, 2018	0.33	0.47	0	1	2894
Ideology	US States	Shor and McCarty, 2011	0.09	0.72	-1.47	1.23	346*
GDP per capita,	National	World Bank, 2016a	17810.61	19575.93	354.28	129349.9	3338
PPP $2011 USD	US States	US BEA, 2016	47576.53	9047.45	31565.52	74417.54	400
	Can. Prov./Terr.	Statistics Canada, 2016c	44510.85	13280	28806.69	95355.49	143
Trade openness,	National	World Bank, 2016a	83.14	49.01	0.02	441.60	3348
% of GDP	US States	U.S. Census Bureau, 2016	18.99	9.64	4.04	59.05	350*
	Can. Prov./Terr.	Statistics Canada, 2016c	57.56	18.55	15.78	111.71	143
CO_2 emissions, t/cap	National	World Bank, 2016a	5.62	7.24	0.017	70.14	3283
	US States	CAIT, 2015	23.6	19.35	8.47	130.7	350*
	Can. Prov./Terr.	Statistics Canada, 2018	20.14	13.23	6.47	52.81	143
Polyarchy	National	Varieties of Democracy, 2018	0.45	0.28	0.01	0.916	3176
Libdem	National	Varieties of Democracy, 2018	0.56	0.27	0.017	0.95	3176
Corruption	National	World Bank, 2016b	0.02	1.05	-2.06	2.59	3150

*The *Ideology* covariate is unavailable for the state of Nebraska and is not available for all years of each panel unit.

*The *Trade openness* and *CO_2 emissions* are unavailable for 2015.

†Includes only jurisdiction-year observations for which a pricing scheme was in operation, i.e. excludes '0' entries which reflect the absence of a pricing scheme rather than a truly zero price.

Source: Authors' calculations.

is the vector of political and institutional variables and $\boldsymbol{W_{it}}$ is the vector of macro(-economic) variables. ϕ_i is the unobserved jurisdiction fixed-effect while d_t is the vector of time dummy variables; $\boldsymbol{\psi'}$, γ' and $\boldsymbol{\eta'}$ are vectors of dimensions m, n and p, respectively, each element of which corresponds to the estimated parameter of the associated explanatory variable. u_{it} and ϵ_{it} are the observation specific error terms.

In estimating 2.1 and 2.2, two potential problems may arise. First, as much as economic structure and electricity generation mix may affect policy implementation and stringency, the latter can also affect the former, creating a reverse causality problem and causing standard estimation approaches to fail. Second, there may be endogenous selection into the policy, which would bias the coefficient estimates in equation 2.2.[20]

Reverse causality The potential presence of simultaneity bias prompts us to: (i) note the features of the data that make our analysis less prone to it, (ii) describe the steps taken to minimize and subsequently address this issue. First, note that $\mathbb{1}_{it}$ records *implementation*, not *passage* of the legislation. In most cases, the year of implementation differs from the year the legislation is passed, the former following the latter by a lag of 1 (in the case of the EU-ETS) to 3 years (in the case of, for example, Chile's carbon tax). This provides a rationale for the use of lagged values of all the variables included as regressors in equation 2.1 – see Table 2.4 – and prevents the possibility that its outcome variable would determine the covariates – at least in a contemporaneous manner. That is, some regressors may only be pre-determined.

Second, an endogeneity problem only arises if the policy, once implemented, works as intended. Carbon pricing policies were primarily designed to affect jurisdictions' CO_2 emissions through altered technological choices or structural changes in the composition of the economy. While it cannot be ruled out that some of these policies (especially the most stringent ones) did have the intended effects, it is worth noting that: (i) these policies affect the economy only slowly, (ii) technological advances in abatement technology may reduce structural shifts in economic composition, (iii) except for a few jurisdictions, most carbon pricing policies introduced over the period covered in the sample have been relatively weak, (iv) several jurisdictions introduced said schemes towards the end of our sample period. All this suggests that it is unlikely that the value added of industry, which we use to proxy for the lobbying intensity of energy-intensive sectors, will be determined by policy implementation or stringency. However, the same argument does not hold as strongly for the electricity mix variables or CO_2 emissions, which tend to be more sensitive to carbon prices.

Selection We only observe the stringency for the jurisdictions that have a scheme in operation in any given year. If there is correlation between the selection (participation) and level/stringency decision, then the process is best modelled as a model with incidental truncation (or selection) where both a level and a selection equation are specified and a correction

[20]Note, however, that a selection bias would only be present insofar as the population of interest is the entire set of jurisdictions initially present in our panels.

for the selection bias is applied (Gronau, 1974; Heckman, 1976). That is, equation 2.2 should be complemented with the introduction of a latent variable (see e.g. Semykina and Wooldridge, 2010):

$$s_{it} = 1[z_{it}\delta_t + \phi_{i2} + v_{it} > 0] \tag{2.3}$$

where 1[.] is an indicator function and s_{it} is a selection indicator that equals 1 if ECP_{it} is observed and 0 otherwise.

Given the above, we implement the following econometric approach, applied to each panel separately. First, we estimate 2.1 with random effect logit and probit models. All regressors in estimations of equation 2.1 are introduced with a two-period lagged value to account for the lag between passage of legislation and policy implementation. Second, we provide results of (FE) OLS and system GMM estimations for equation 2.2. In addition to controlling for unobservable time-invariant fixed effects, the GMM estimator allows us to account for potential endogeneity of the regressors and model the persistence of the stringency variable. The GMM approach has been taken in Marques and Fuinhas, 2011 to study the relationship between a very similar set of covariates and renewable energy deployment.

We correct for the selection bias by introducing a sample selection correction term. This term is calculated for each ECP observation using a Heckit approach adapted from Semykina and Wooldridge, 2010. In a first step, a probability of occurrence of that observation is obtained by estimating, for each t, equation 2.3 using a probit regression on the entire cross-section of jurisdictions. In a second step, this term is then included in the estimation of equation 2.2 as a regressor. For panel A, the set of regressors for the selection equation includes the electricity generation mix variables, the value added of industry, CO_2 emissions and GDP per capita, trade openness, and *EU*.[21] All variables are introduced with a two-year lag to reflect our theoretical assumption that operation of a carbon pricing scheme ($s_{it} = 1$) is dictated by past economic and institutional structure. For panel B, the same variables are included, except *EU*.[22]

2.6 Estimation results

We comment separately on the estimation of equations 2.1 and 2.2. The results are presented for panels A, B and C. All estimations include year fixed-effects, and all estimations of equation 2.2 include country fixed-effects.

2.6.1 Implementation

Panel A – National jurisdictions Table 2.4 presents the results of both RE logit and RE probit estimations, which lead to convergent conclusions about the effects of the covariates on the

[21] Institutional capacity and *Left* are not part of the selection equation since the former is not available until 1997 and the latter further reduces the panel dimension.

[22] Given the paucity of ECP observations for Canadian Provinces & Territories (2 panel units, for a total of 9 observations) no estimation is presented.

decision to implement a carbon pricing scheme. First, estimates suggest that a larger share of electricity generated from gas and oil fired power plants lowers the probability of subsequent introduction of a carbon pricing scheme. This is in line with our expectation that jurisdictions whose electricity generation system relies more heavily on fossil fuels would face greater opposition to the introduction of such schemes. The estimates of the coefficient on the share of coal in the electricity system, however, do not indicate a consistent pattern of influence on the implementation of carbon pricing mechanisms, which runs against the understanding that jurisdictions with coal fired electricity systems would fiercely oppose the introduction of carbon pricing policies. One potential explanation for this is that 'dirty' electricity producers have been granted significant compensation in the schemes introduced so far. For example, in the case of the EU-ETS, CO_2-intensive electricity producers and heavy industries were 'bought in' by grandfathering emissions allowances in the first two phases of the operation of the system. Second, within the sample of national jurisdictions, we find little evidence supporting the hypothesis that larger industry or manufacturing sectors hindered the introduction of carbon pricing policies. Although coefficient estimates are negative across all estimations, they are only weakly statistically different from zero. One potential explanation for this observation is that the set of panel units includes both strongly industrialized and less industrialized jurisdictions, with most carbon pricing policies having been introduced within the former group. Lastly, trade openness does not seem to have played a determining role in the introduction of carbon pricing policies. Again, one can plausibly suggest that it is related to the fact that existing schemes have: (i) covered non-traded sectors; (ii) provided sectoral exemptions/compensation for industries exposed to international competition. Third, the institutional environment does play a role in the adoption of carbon pricing policies. Results suggest a consistent pattern of introduction of carbon pricing policies among jurisdictions that rank higher on the Polity IV democracy index and have a stronger institutional capacity as calculated in this chapter. This partially supports the hypothesis formulated by Congleton, 1992 that democratic institutions are conducive to more stringent environmental regulations (*a* carbon price, regardless of its level, is a more stringent policy than *no* price at all) and lends support to Hahn (1990) 's conclusions that environmental regulation is a balancing act between a variety of interests (the actual stringency is determined by the relative weight of each interest group and not by the 'democratic' nature of a political system). This might also suggest that the 'green' lobby is effectively given some weight in the policy making process. The economic orientation of the executive does not seem, on the contrary, to play a significant role in the adoption of carbon pricing policies, suggesting that, in the sample currently considered, such policies have received support from parties across the political spectrum. This result is in line with Fankhauser, Gennaioli, and Collins, 2015. The results also highlight the (international) institutional dynamics at play in the development of carbon pricing policies as EU membership is found to strongly affect the probability of introduction of a carbon pricing scheme, an result that is likely to be mainly driven by the introduction of the EU-ETS in 2005. The results also indicate that, all else equal, larger emitters (per capita) have been more to likely introduce carbon pricing mechanisms, reflecting the fact that, until now, carbon pricing mechanisms have been introduced in more economically advanced jurisdictions with large CO_2/capita emissions, possibly following international commitments. Finally, GDP per capita has a positive effect on the introduction of a carbon pricing mechanism (I and III), although the statistical significance of this effect vanishes when institutional capacity is accounted for (II and IV). Its magnitude changes depending on the econometric specification but the direction of the induced change is stable across all estimated models, strongly suggesting that economic agents are more likely to support the introduction of such policies if they are relatively better off.

TABLE 2.4: Implementation – Outcome: $\mathbb{1}$

Panel	Category	Variable	RE Logit		RE Probit	
			(I)	(II)	(III)	(IV)
A - National	Regulatory capture – X	Power-Coal$_{t-2}$	-0.014	-0.016	0.01	0.043
			(0.0355)	(0.0358)	(0.0165)	(0.0184)
		Power-Gas$_{t-2}$	-0.065*	-0.096	-0.029	-0.063*
			(0.0467)	(0.0616)	(0.0207)	(0.0359)
		Power-Oil$_{t-2}$	-0.286***	-0.188***	-0.109***	-0.132***
			(0.0812)	(0.0775)	(0.0332)	(0.0434)
		Industry, VA$_{t-2}$	-0.141	-0.114	-0.06	-0.054
			(0.1319)	(0.2163)	(0.0706)	(0.0943)
		Trade Openness$_{t-2}$	0.023	0.008	0.01	0.01
			(0.0198)	(0.023)	(0.0087)	(0.0147)
	Political institutions – Z	Level of Democracy$_{t-2}$	1.756***	0.82***	0.759***	0.834***
			(0.2229)	(0.4216)	(0.0972)	(0.2363)
		EU$_{t-2}$	14.449***	17.9***	5.643***	11.249***
			(4.1656)	(3.2755)	(1.5721)	2.095
		Left$_{t-2}$		-1.209		-0.564
				(1.4653)		(0.8598)
		Institutional capacity$_{t-2}$		7.423**		5.925***
				(3.0055)		(1.6916)
	Macro(economic) environment – W	GDP per cap.$_{t-2}$	0.397***	0.093	0.167***	0.125**
			(0.0489)	(0.1014)	(0.0306)	(0.0599)
		CO_2 Em$_{t-2}$	0.153	0.199	0.045	0.036
			(0.1575)	(0.2003)	(0.0812)	(0.1103)
		Constant	-46.352***	-42.879***	-20.257***	-33.924***
			(7.3768)	(9.8192)	(3.7665)	(4.8143)
		Year dummies	Yes	Yes	Yes	Yes
	Observations		2726	1793	2726	1793

Standard errors in parentheses – * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: (i) The institutional capacity variable is observed for the first time in 1997, shortening the time dimension of models (II) and (IV). Together with the lower number of panel units available for *Left*, it explains the lower number of observations; (ii) all time dummies from 2005 onwards were statistically significant at the 1% level in models (I) to (IV). We also took a different approach and introduced a time trend. It did not, however, exhibit any significance. Source: Authors' calculations.

Panels B & C – US States & Canadian Provinces The results for the subnational jurisdictions (Table 2.5) considered are broadly consistent with those based on panel A, although we note some interesting differences.[23] In the US, results indicate that electricity generation from fossil fuels negatively impacted the development of carbon pricing mechanisms, with the largest

[23]Panel B contains only *Ideology* as political variable and panel C contains no variable reflecting the state of political institutions.

absolute effect associated with electricity generation from oil. The results also suggest that carbon pricing mechanisms were less likely to be introduced in states with high CO_2 emissions per capita as well as states for which (CO_2-intensive) industry represents a large share of total economic activity – consistent across models (V) and (VI). Conversely, states with relatively higher income per capita were more likely to introduce carbon pricing. The insights obtained from panel C need to be interpreted with caution as only two Canadian Provinces introduced a carbon pricing mechanism over our sample period. Nonetheless, results suggest that richer (per capita) jurisdictions were more likely to introduce carbon pricing mechanisms whereas larger CO_2 emitters (per capita) or jurisdictions with relatively larger industry were less likely to do so. In that regard, it is interesting to note the contrasted dynamics between national and subnational jurisdictions. For example, national jurisdictions with large CO_2 emissions (per capita) seem to have taken the lead in pricing carbon (perhaps due to international commitments) whereas large (per capita) subnational emitters have not.

2.6.2 Stringency

This section discusses the estimation results of equation 2.1. Tables 2.6 and 2.7 present the results for national jurisdictions and US States, respectively. Models VII and IX do not account for potential sample selection bias whereas models VIII and X do. The results clearly demonstrate a very high persistency of policy stringency. This effect is present across all panels, consistent across estimators and of the order of 0.8-0.9, indicating that carbon pricing policy stringency changes very slowly over time. The evidence regarding the role of the electricity generation portfolio is mixed. In panel A, electricity generation from coal is found to have a negative impact on the stringency of implemented schemes only in models IX and X. The associated estimated coefficients suggest that an increase of 10% in the share of electricity generated from coal would lead to a 0.6-1.2USD/tCO_2e decrease in the average carbon price. Similar mechanisms are identified for the share of gas in the electricity generation mix, which weighs negatively on the stringency of the carbon pricing policy. A 10% increase in this share would reduce the average carbon price by between 0.9USD/tCO_2e and 1.8USD/tCO_2e. Next, coefficient estimates of all models except model IX point at a negative effect of the relative strength of industry on the policy stringency. The magnitude of this negative effect varies from -0.17USD/tCO_2e in model X to -0.04USD/tCO_2e in model VIII for each 1% increase in the share of industry in total GDP. Results do not support the existence of a clear relationship between trade openness and policy stringency, most likely for the same reasons that it did not seem to decisively affect implementation. Interestingly, results indicate that being part of the EU had a positive yet not statistically significant impact on stringency. The magnitude of the estimated effect varies greatly across models VII-X, with the largest effect is estimated in model X, at about 10USD/tCO_2e. Finally, the effect of CO_2 emissions per capita is not clearly identified, being negative in models VII and VIII where estimates may suffer from simultaneity bias, and positive yet with weak statistical significance in models IX and X.

TABLE 2.5: Implementation – Outcome: $\mathbb{1}$ (cont.)

Panel	Category	Variable	RE Logit (V)	RE Probit (VI)
B – US States	Regulatory capture – $\boldsymbol{X}$	Power-Coal$_{t-2}$	-0.225	-0.086
			(0.1489)	(0.1041)
		Power-Gas$_{t-2}$	-0.082	-0.014
			(0.0706)	(0.05)
		Power-Oil$_{t-2}$	-0.308	-0.222
			(0.4222)	(0.2352)
		Industry, VA $_{t-2}$	-1.71**	-1.111*
			(0.7826)	(0.6487)
		Trade Openness$_{t-2}$	0.305	0.206
			(0.1866)	(0.1341)
	Political institutions – $\boldsymbol{Z}$	Ideology$_{t-2}$	-0.031	0.004
			(3.1119)	(1.9761)
	Macro(economic) environment – $\boldsymbol{W}$	GDP per cap.$_{t-2}$	0.738**	0.386**
			(0.3176)	(0.176)
		CO_2 per cap.$_{t-2}$	-1.509**	-1.154*
			(1.3175)	(0.6273)
		Constant	14.929	13.891
			(37.9157)	(16.2831)
		Year dummies	Yes	Yes
	Observations[a]		255	255
C – Canadian Prov. & Territories	Regulatory capture – $\boldsymbol{X}$	Power-Coal$_{t-2}$	0.544	0.208
			(0.8818)	(0.4137)
		Power-Gas$_{t-2}$	1.093	0.481
			(0.6613)	(0.3694)
		Power-Oil$_{t-2}$	-5.5328	-1.918
			(4.0517)	(1.8411)
		Industry, VA$_{t-2}$	-0.193	-0.092
			(1.1889)	(0.3729)
		Trade Openness$_{t-2}$	-0.405	-0.159
			(0.3713)	(0.1843)
	Macro(economic) environment – $\boldsymbol{W}$	GDP per cap.$_{t-2}$	0.556	0.271
			(0.748)	(0.3140)
		CO_2 per cap.$_{t-2}$	-0.994	-0.338
			(2.0007)	(0.9613)
		Constant	-14.086	-4.699
			(19.9356)	(10.8357)
		Year dummies	Yes	Yes
	Observations[a]		117	117

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Panel A: from a number of observations of 400, we lose 2x50 observations given that we use two-years lag. Panel B: 2x13 observations are lost. Year dummies from 2012 onwards are significant in Panel B estimations. None of the year dummies for panel C were significant. Source: Authors' calculations.

Insights from panel B point to a similarly persistent stringency process, with a coefficient estimate for ECP_{t-1} of 0.90 in model XIV. Estimates in models XI and XII are most likely severely biased due to the short time dimension of Panel B. The results also suggest that larger CO_2 emitters and more industrious (CO_2-intensive) US States had more stringent carbon pricing mechanisms. These effects are, however, not statistically significant when estimated with the GMM estimator.

TABLE 2.6: Stringency – ECP (2015 \$US/tCO_2e)

Panel	Category	Variable	FE OLS (VII)	FE OLS, Heck (VIII)	Syst GMM (IX)	Syst GMM, Heck (X)
A – National		ECP_{t-1}	0.875***	0.879***	0.824***	0.824***
			(0.0438)	(0.052)	(0.1126)	(0.1402)
	Regulatory capture – $\boldsymbol{X}$	Power-Coal$_t$	0.068**	0.064*	-0.0554	-0.123
			(0.0261)	(0.0324)	(0.0773)	(0.1106)
		Power-Gas$_t$	0.022	0.03	-0.088*	-0.181*
			(0.0274)	(0.0268)	(0.0508)	(0.0911)
		Power-Oil$_t$	-0.016	-0.013	0.095	0.061
			(0.1084)	(0.1089)	(0.1265)	(0.1609)
		Industry, VA$_t$	-0.084	-0.041	0.068	-0.173
			(0.1021)	(0.0918)	(0.2857)	(0.4142)
		Trade Openness$_t$	-0.014	-0.021	0.02	0.028
			(0.0239)	(0.0242)	(0.026)	(0.0427)
	Political institutions – $\boldsymbol{Z}$	EU$_t$	0.621	0.127	3.801	10.412
			(1.0813)	(0.8366)	(6.101)	(7.9493)
	Macro(economic) environment – $\boldsymbol{W}$	CO_2 Em$_t$	-0.533**	-0.473**	0.458	0.453
			(0.2058)	(0.199)	(0.5451)	(0.6637)
		Constant	6.186	7.861	5.499	9.1
			(4.0966)	(3.6756)	(16.577)	(20.9732)
		Year dummy	Yes	Yes	Yes	Yes
		Sample selection term	No	Yes	No	Yes
		Instruments			GMM-sys	GMM-sys
		Observations	349	349	349	349
		AR(1) test			-3.38***	-2.79***
		AR(2) test			0.64	0.16
		Sargan (χ^2)			10.12	3.95

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time dummies for years 2005 and 2007 to 2010 were significant in models (VII) and (VIII) but not in models (IX) and (X).
Including GDP in the stringency equation does not qualitatively nor quantitatively change the results.
The sample selection terms are significant in regressions (VIII) and (X). Source: Authors' calculations.

2.6.3 Robustness checks and discussion

2.6.3.1 Robustness checks

To test the robustness of our results, we perform a series of additional estimations. First, to address concerns that the coefficient estimates of equation 2.1 may be biased due to correlation between past residuals and current regressors, we repeat its estimation with a sample where, for each panel unit, the time dimension is (right)-curtailed at the year of policy adoption. That is, for each panel unit in which a carbon pricing scheme was introduced, we keep only one observation for which $\mathbb{1} = 1$. The results are qualitatively similar, although statistical significance of the estimated coefficients decreases. Second, we note that for equation 2.1, i.e. regression models I to VI, the results do not change qualitatively if we choose a different (meaningful) lag structure. In particular, they are robust to the use of one-period lagged values of the regressors. Third, it can be argued that, over the period considered, there exists a structural break in carbon pricing policy developments as many national jurisdictions introduced such policies after 2005. To test whether the dynamics presiding over these developments differ prior and after 2005, we re-estimate models II and IV over two different time periods: 1990-2004 and 2005-2015. For the period 1990-2004, the share of electricity generated from gas and oil is negatively associated with the probability of implementation of carbon pricing policies. Surprisingly, the

TABLE 2.7: Stringency – ECP (2015 \$US/tCO_2e) (cont.)

Panel	Category	Variable	FE OLS (XI)	FE OLS, Heck (XII)	Syst GMM (XIII)	Syst GMM, Heck (XIV)
B – US States		ECP_{t-1}	1.042***	1.038***	0.88***	0.903***
			(0.0815)	(0.0907)	(0.0462)	(0.0728)
	Regulatory capture – $\boldsymbol{X}$	Power-Coal$_t$	-0.014*	-0.014*	-0.004	-0.005
			(0.0076)	(0.0076)	(0.0051)	(0.0046)
		Power-Gas$_t$	-0.001	-0.0014	0	0.001
			(0.0037)	(0.0037)	(0.0045)	(0.0066)
		Power-Oil$_t$	0.025	0.027	0.142***	0.137***
			(0.0316)	(0.0349)	(0.045)	(0.0488)
		Industry, VA$_t$	0.018***	0.018**	0.011	0.014
			(0.0057)	(0.006)	(0.0072)	(0.0149)
		Trade Openness$_t$	0.032***	0.032***	0.006	0.011
			(0.0077)	(0.0077)	(0.0132)	(0.0177)
	Macro(economic)	CO_2 Em(Mt)$_t$	-0.025	-0.024	0.074	0.079
	environment – $\boldsymbol{W}$		(0.0254)	(0.0265)	(0.0585)	(0.069)
		Constant	-0.573	-0.577	-	-
			(0.4375)	(0.39)		
		Time dummies	Yes	Yes	Yes	Yes
		Sample selection	No	Yes	No	Yes
		Instruments			GMM-sys	GMM-sys
		Observations	49	49	49	49
		AR(1) test			1.51	0.09
		AR(2) test			1.27	0.23
		Sargan (χ^2)			39.47***	18.62***

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All year dummies are statistically significant at (at least) the 5% level in models (XI) and (XII). In models (XIII) and (XIV), year dummies 2010 and 2011 are not significant; all others are. Source: Authors' calculations.

share of electricity produced from coal seems to have a small positive – albeit statistically insignificant – impact. This may be driven by the fact that Denmark, which was in 1990 heavily reliant on coal for its electricity generation, managed to introduce a carbon pricing mechanism in 1992 (albeit with substantial sectoral exemptions and rebates). The more general observation that electricity generation from fossil fuels weighted negatively on carbon pricing policy developments may reflect the fact that until 2004, only northern European jurisdictions, which have achieved a lower share of electricity generated from fossil fuel over time, had introduced a carbon pricing scheme. In addition to this, the coefficient of *EU* is an order of magnitude smaller than in the full sample models. This is likely explained by the fact that carbon pricing activity took place in jurisdictions that were not EU members at the start of the scheme. Over the period 2005-2015, the results for these models indicate that EU membership was a much more significant determinant of the introduction of carbon pricing mechanisms. This echoes the fact that a lot of these jurisdictions' first carbon pricing mechanism was the EU-ETS. GDP per capita, institutional capacity and the level of democracy are both found to positively affect implementation over the period whereas the share of industry, CO_2 emissions per capita and the orientation of the executive with respect to economic policy have a negative impact on implementation. All coefficient estimates except those associated with GDP and the level of democracy exhibit, however, weak statistical significance.

We also checked whether the results were robust to the use of different indicators of democratic institutions, namely *Polyarchy* and *Libdem*, as well as with another indicator of governance, *Corruption*. Estimations of models I to IV with these variables provided very similar results, which is somewhat unsurprising given that these are highly positively correlated with our main indicator of democratic institutions ($\rho = 0.9$ and $\rho = 0.85$, respectively). Estimations with the (control of) corruption variable suggested that implementation of carbon pricing policies was more likely to occur in less corrupt jurisdictions. Finally, we repeated the estimation of regressions VII to X with a different version of our outcome variable in equation 2.2, one where the weights are varying year-to-year. The results are, for all models considered, qualitatively similar.

Lastly, we note that neither the main estimations nor the robustness checks allow for heterogeneity in estimated parameters across (groups of) jurisdictions (beyond jurisdiction Fixed Effects). Yet, the relationships estimated above might differ across (groups of) jurisdictions. If differences in institutions or economic structure across (groups of) jurisdictions cannot be reasonably accounted for in econometric specifications, then splitting the estimation sample between specific groups might provide group-specific estimates. However, given that most jurisdictions with carbon pricing in our sample are industrialised countries, we have not, at this stage, considered such heterogeneity. While this aspect is not explored in the present chapter, it could add to our understanding of the dynamics at play, especially once the number of jurisdictions with active carbon pricing policies has increased.

2.6.3.2 Discussion

Further to the robustness checks carried out and discussed above, we make three additional observations based on the results of our analysis. First, we note that despite us taking great care to reduce the risk of simultaneity bias, the nature of the question at hand, i.e. what determines a jurisdiction's adoption and stringency of carbon pricing policies, and the resulting econometric specification render strong causal claims as to the relationships identified difficult, especially for the stringency equations. We note, however, that this does not jeopardise the main conclusion drawn from our results on the stringency equations: that stringency is a highly persistent AR(1) process.

Second, the present analysis focuses on jurisdiction-level policy adoption and does not seek to distinguish between tax and emissions trading schemes. It constitutes a first attempt at identifying some systematic patterns of adoption of such policies. A more refined understanding could be obtained by (i) looking at sector-level policy adoption and stringency across jurisdictions and (ii) distinguishing between the dynamics of adoption of tax and emissions trading schemes. It is indeed to be expected that the political economy of carbon pricing might differ across sectors and/or types of instrument, not least because of different (distributional) implications of these instruments for the affected sectors and/or their ability to affect the design of either instruments in ways favourable to them.[24]

Finally, there have been several failed attempts at introducing carbon pricing schemes in both national (e.g. Australia) and subnational (e.g. Washington State in the US) jurisdictions. While the results presented in this study help shed some light on these failures, it is likely that local/idiosyncratic factors would go a long way in explaining them further. As such, identifying these factors would require more in-depth jurisdiction/scheme-specific case studies.

2.7 Conclusions

Carbon pricing policies have re-emerged in the policy making arena as potential tools to achieve (some) reductions in GHG emissions. This renewed political appetite for carbon pricing mechanisms is apparent in the number of new schemes brought online over the last decade. However welcome these developments are, they should not be understood to mean that carbon pricing policies are on track to expand quickly to new jurisdictions nor to reach the stringency that achieving the Paris Agreement target requires. Indeed, this chapter shows that, when weighted for the share of covered emissions, these policies are, in most jurisdictions, much weaker than typically assumed. Moreover, because the jurisdictions with carbon pricing policies represent a small share of world emissions, the world average price of emissions remains extremely low, at about 1USD/tCO_2e in 2015. In light of the statistical results discussed in this study, this is an uncomfortable state of affairs. First, because structural political and economic forces continue to hinder the introduction of new schemes beyond jurisdictions for which the political and economic cost of pricing carbon is comparatively low. For example, carbon pricing is unlikely to appeal to jurisdictions with low GDP per capita and/or, oil-fuelled electricity generation, for which other domestic policies, possibly complemented by international technology and financial transfers would prove more palatable. Second, because all implemented schemes exhibit strong persistency in their stringency, which is particularly problematic given that most of the schemes introduced so far are associated with weak (average) price signals.

The present analysis does, however, also offer lessons – and cautious optimism – for future policy developments. First, even if such developments are hindered by political economy factors, their effect is not as strong as one might have initially expected and suitable policy designs have been found to overcome them. Nonetheless, the difficulty with which carbon pricing schemes can be introduced, together with the weakness of most existing ones continues to provide a rationale for the development of climate mitigation strategies with multiple GHGs abatement tools and stresses the need to carefully consider the private and public cost of (early) retirement of the existing capital stock. This also highlights the importance of the sequence of introduction of the climate change mitigation policy package. One way to weaken

[24] Aldy and Stavins, 2012, argue, however, that one advantage of cap-and-trade programs over tax schemes is that political pressures on the latter lead to sector and firm exemptions that decrease environmental effectiveness and raise total costs of emissions reduction; whereas political pressure on the former lead to changes in the distribution of the burden but do not raise total costs nor decrease environmental effectiveness.

incumbents' lobbying power is to weaken their relative influence *prior* to the introduction of carbon pricing policies.

Second, even in the presence of other climate policies, this analysis suggests that there is room for further strengthening of carbon pricing mechanisms. This can be done through extension of coverage or a price increase in currently covered sectors. But when considering implementation or strengthening of carbon pricing schemes, jurisdictions ought to pay close attention to the factors discussed here as it may save them from spending time and political capital on policy proposals bound to be met by fierce opposition.

Chapter 3

Climate policy diffusion: theory and evidence

3.1 Introduction

Limiting the increase in Global Mean Temperature to 2°C above pre-industrial levels will require drastic reductions in GHG emissions. Since CO_2 is a *global* pollutant, any environmentally effective solution requires a reduction in 'world' emissions. However, no World Government capable of enforcing worldwide reductions in GHG emissions exists. Instead, a multitude of sovereign states interact within the Westphalian system of International Relations and its founding principles (self-determination, legal equality of States and no third-party interference in internal affairs) make cooperation the only available option to efficiently address global public good problems like Climate Change (Barrett, 2003). It is precisely these principles – and their implications – that shaped the UNFCCC, formally established in 1992.

In light of this observation, Parties to the Convention initially adopted a cooperative approach to emissions reduction and sought to design multilateral agreements that could sustain the cooperative outcome. In line with these developments and following Carraro and Siniscalco, 1997, a substantial body of research explored the conditions for (stable) *climate coalition* formation. However, notwithstanding mechanisms to improve the stability of such coalitions (Nordhaus, 1989) and as predicted by standard game theoretical discussions of environmental agreement negotiation (Barrett, 1994), this *top-down* cooperative approach failed to deliver emissions reductions consistent with stated objectives of global average temperature increase.[1] In this context, jurisdictions at best offered to implement their Nash equilibrium strategy, committing to (very) low, globally sub-optimal, levels of emissions reductions, while others simply did not commit to any reduction at all.[2]

[1] See Chapter 2.

[2] Incentives for unilateral provision of global environmental quality beyond the Nash equilibrium outcome have so far proven relatively weak. These can be broadly grouped into altruistic (e.g. self-enforcing collective identity (Olson, 1965), rule utilitarianism (Harsanyi, 1977), different domestic preferences, or genuine care for the global environment) and self-interested (e.g. strategic innovation,. . .).

Taking stock of this relative failure, the Paris Agreement shifted the architecture of international climate negotiations from a cooperative to a non-cooperative setting: under its provisions, Parties are invited to submit their Intended Nationally Determined Contributions (INDCs) to the achievement of the stated temperature warming objective. With such an institutional design, the key questions no longer pertain to the formation of climate coalitions and the mechanisms to sustain them but rather to the determinants of unilateral climate change mitigation policy ambition. In this respect, the Agreement implicitly acknowledges that technological demonstration and policy learning are such determinants. Indeed, parts of it rest on the premise that by offering to Parties the flexibility to put forward strategies based on a variety of abatement policies and technologies, it will foster their demonstration and diffusion across sectors and jurisdictions (Paris Agreement, Art. 6-1, 6-8, 7-6, 7-7, 10) and, ultimately, trigger increased climate policy ambition.

Yet, even if there are good reasons to believe that such diffusion processes might be at play – for example, the evidence accumulated since the implementation of the first carbon pricing scheme in Finland in 1990 suggests that the adoption of such schemes is highly clustered both temporally and spatially (see Figure 3.1)[3], the precise mechanisms of diffusion, if at all present, remain ill-understood. An improved understanding of these mechanisms would not only shed a new light on past developments but also provide insights into the chances of success of the Paris Agreement architecture.

To this end, we start by noting that, until now, jurisdictions looking to implement new climate change mitigation policies (or strengthen existing ones) have been primarily concerned with (i) free riding and the international competitiveness of domestic GHG-intensive sectors, (ii) the cost (and availability) of GHG-abatement technologies and (iii) the uncertainty surrounding the political and economic implications of such policies. Each of these concerns have contributed to keeping climate change mitigation ambition low. Yet, in recent years, the cost of GHG-abating technologies plummeted as some jurisdictions embarked on their development and deployment, while the adoption of (more stringent) climate change mitigation policies by an increasing number of jurisdictions alleviated international competitiveness concerns and provided additional information on (successful) policy designs. As detailed further through this chapter, these developments could trigger increased policy ambition by individual jurisdictions.

Following Simmons and Elkins, 2004, we hypothesise that the processes of policy diffusion are related to two main mechanisms. First, an alteration of the net payoffs of domestic climate policy, which takes place through (a) a technology channel – abatement technology development, and subsequent diffusion, by foreign jurisdictions reduces the cost of emissions reduction (see, e.g., Heal, 1993); and (b) a policy (adoption) channel – which alters the magnitude of free riding and the international competitiveness cost of more stringent domestic environmental

[3] According to World Bank, 2018, 5 carbon pricing schemes were introduced between 1990 and 1992, 12 (including the EU-ETS) were introduced over the period 2005-2011 and 26 were introduced between 2012 and 2018.

policy.[4] Second, an update on the information about the benefits (or costs) of policy adoption derived from the adoption of a similar policy or the deployment of abatement technology in foreign jurisdictions. This information could be communicated through different cultural or institutional affiliation channels (e.g. EU, OECD,. . .).[5]

In other words, alongside standard international trade considerations, this chapter relates the adoption of new climate change mitigation policies – or raised climate change mitigation policy ambition – to the (pre-)existence of technology and information diffusion networks via which technology development and deployment as well as policy adoption by one jurisdiction spills-over to other jurisdictions. Importantly, we note that the hypothesised mechanisms of diffusion are not necessarily clear *a priori* but that the chapter is grounded in a static general equilibrium model based on Copeland and Taylor, 2003 which explicitly accommodates them. Using this framework as a guide for our empirical investigation, these hypotheses are then tested on a comprehensive dataset containing information on climate and carbon pricing policy developments over 25 years in a panel of national jurisdictions.

The remaining of this chapter is organised as follows. Section 3.2 reviews the relevant strands of literature. Section 3.3 introduces a formal framework to support our empirical discussion; section 3.4 builds on it to introduce the hypotheses. Section 3.5 presents the data and the modelling strategy and section 3.6 presents the results. Finally, section 3.7 concludes.

3.2 Related literature

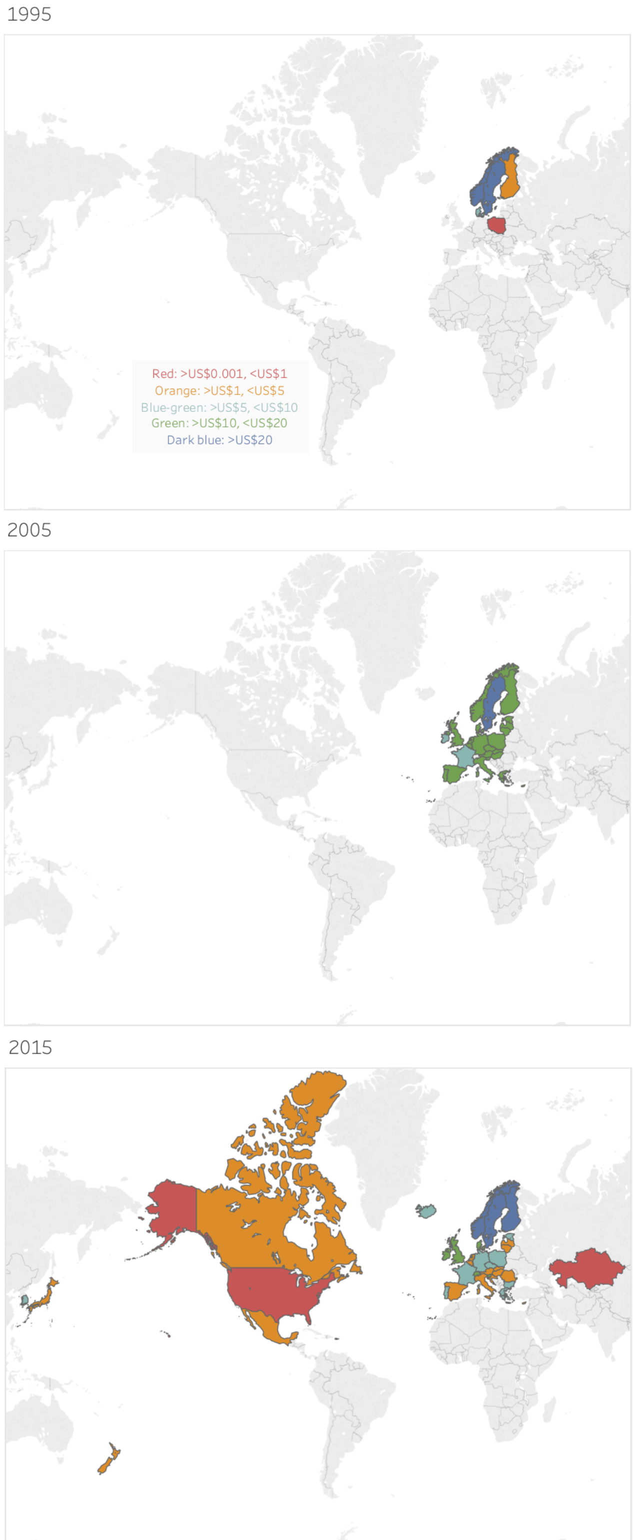
The literature on policy diffusion offers a route to rationalise the latest carbon pricing and climate policy developments. In particular, unlike standard political economy studies of the development of environmental – and other – policies which usually focus on domestic conditions in their attempt to rationalise policy developments, this literature emphasises the importance of foreign developments for domestic policy making, mainly through changes in the net payoffs or updated informational signal that policy adoption implies (see Fankhauser, Gennaioli, and Collins, 2015 and references therein). Given the global nature of the GHG externality and the multi-dimensional interdependence of jurisdictions, it is indeed unlikely that domestic factors alone will drive climate policy developments. We focus on three determinants that are likely to shape domestic climate policy decision(s) and be influenced by international developments: (i) other jurisdictions' policies, especially those of (trade) partners; (ii) the techno-economic context, in particular the cost and availability of abatement technology; (iii) the expected (political) cost of policy implementation. We briefly review the literature associated with each of them.

Standard economic analysis of global pollutants regulation in an international (trade) context points at the presence of both free riding and leakage effects (Copeland and Taylor, 2005),

[4]For example, the international competitiveness disadvantage created by more stringent carbon pricing policy is alleviated when all members of a 'closed' trading club implement it. Such a club could be closed *de facto* – in case a group of countries trade mostly among themselves – or *de jure* – in case a group of countries implements external CO_2 adjustment tariffs (see, e.g., Nordhaus, 1989).

[5]In addition, the strength of these mechanisms depends on the nature and intensity of the relationship between bilateral partners (or, in other words, "distance").

FIGURE 3.1: Adoption of carbon pricing policies in national jurisdictions: 1990-2015



Note: a light grey shade indicates the absence of any carbon pricing scheme; The figure for Canada and US is the country-wide average price resulting from carbon pricing schemes implemented at the Provincial or State level which have greatly concerned policy makers in jurisdictions that considered stringent climate change mitigation policies. This literature proposes discussions based on considerations of relative input factor endowments, relative international prices, . . . (see, e.g. Antweiler, Copeland, and Taylor, 2001) and suggests that domestic environmental regulation affect trade patterns.[6]

Next, the role played by abatement technology is the motivation behind discussions around its institutionalised transfer between (groups of) jurisdictions (e.g. UNFCCC, Article 4.5) and provides the rationale for a substantial body of work that seeks to shed light on channels of (abatement) technology diffusion.[7] This literature has mainly focused on bilateral transfers of technology across jurisdictions and has noted three main market channels: (i) international trade in intermediate goods (e.g., export and import of equipment) – Grossman and Helpman, 1991 have previously argued that knowledge varies according to the number of contacts between domestic and foreign agents and that these contacts are directly proportional to trade flows; (ii) foreign direct investments – for example, multinational corporations can bring home country clean production techniques to host countries; (iii) licensing.

Finally, governments often lack sufficient understanding of the consequences of a particular policy innovation (Simmons and Elkins, 2004), in which case *inaction* may simply reflect a lack of accurate information. Climate policy adoption by better informed jurisdictions may serve as a signal about the (low) cost of the said policy, prompting a jurisdiction to “mimick" its (close) neighbour.

The policy diffusion framework that we suggest accounts for factors that standard economic analysis deems relevant to the shaping of domestic climate policy – such as factor endowments and international prices – and the availability of abatement technology – as well as factors usually put forward by the literature on policy diffusion – such as policy learning. In doing so, it extends the policy diffusion literature, which usually focuses primarily on the altered payoff or informational signal following from the adoption of the same policy in partner jurisdictions and furthers our understanding of climate policy adoption. The theoretical framework used to support our argument is presented in the next section.

3.3 Theoretical framework

We cast our discussion within a stylised multi-country (jurisdictions are indexed by $i = 1, 2, \ldots, n$.) two factors $\mathbf{r} = (r_1 = K, r_2 = L)$ - two goods $\mathbf{t} = (t_1 = x, t_2 = y)$ general equilibrium model of

[6] This latter literature formulates two main hypotheses. The *pollution haven hypothesis* which states that, insofar as environmental regulation raises the cost of manufacturing goods, pollution-intensive economic activity will relocate to jurisdictions with lower environmental standards, and the *factor endowment hypothesis*, which claims that standard forces such as factor endowments and technology determine the pattern of trade, not (only) environmental policy (Copeland and Taylor, 2003). Several empirical studies have provided evidence in support of the second hypothesis and, de facto, cast serious doubt on the first (Tobey, 1990; Grossman and Krueger, 1993; Jaffe et al., 1995).

[7] The focus of this paper is on the role played by bilateral relationships and, in that respect, differs from approaches adopted, for example, by Vega and Mandel, 2018. Their approach “accounts for the impact of each country not only on its direct connections, but also on the global diffusion process" (p.462).

international trade with transboundary pollution, adapted from Copeland and Taylor, 2003.[8] We distinguish between primary factors of production and consumption goods (Dixit and Norman, 1980). Primary factors are non tradable while goods are. Labour is mobile across sectors but not across countries.

We assume that n is large and that all countries have the same *relative* size so that each country cannot, individually, influence its terms of trade (Grossman and Helpman, 1991).[9] The model is static, productive factors are in inelastic supply and environmental quality is a global public good.[10] Finally, factor endowments vary across countries and determine trade patterns.

3.3.1 Technology

We assume strictly concave, constant returns to scale technology (CRS) and linearly homogenous production functions for both goods. That is, the set of technologically feasible (r, t), T, is convex. The production of good x generates pollution, e, as a by-product while the production of good y doesn't.[11] The production function of the clean good y is:

$$y = F(K_y, L_y) \tag{3.1}$$

The presence of a clean good allows us to make a clear distinction between (i) sector-level and (ii) economy-wide impacts of the diffusion mechanisms we consider in this paper. For instance, as we discuss in more detail in section 3.4.2 and appendix B.3, an improvement in abatement technology will affect the dirty sector directly as well as induce a reallocation of productive resources between the dirty and the clean sector.

In industry X, abatement activity is considered to be costly to firms. That is, firms produce potential output $B(K_x, L_x)$ and can choose to redirect a fraction $\phi \in [0, 1]$ of inputs to the abatement process, which will, in turn, reduce the net output of good x. In other words, the net production of x is the difference between potential production and production foregone due to the use of resources in abatement activity, $(\phi K_x, \phi L_x)$. As a result, emission intensity in that

[8] The two main adjustments are (i) an explicit recognition of the role played by (improvements in) abatement technology in the determination of domestic climate policy, and (ii) a reinterpretation of the regulatory threshold as depending on expectations about the (economic and/or political) cost of policy intervention.

[9] While assuming away the influence of domestic environmental policy on world prices excludes the possibility for policy makers to manipulate their terms of trade by their choice of climate policy, it allows us to keep the argument focused on the mechanisms of interest. Strategic setting of environmental policy for the purpose of manipulation of the terms of trade is not considered here.

[10] The mechanisms under consideration in this chapter are dynamic in nature (e.g. accumulation of knowledge or abatement technology over time). However, so long as the policy decision is influenced by the accumulated stock rather than flow variables and that there are no inter-temporal strategic interactions, a static model is sufficient to capture the essence of the the problem at hand.

[11] This is without loss of generality and it can easily be extended to a context with $m > 2$ goods exhibiting different emissions intensities. In other words, our framework and results would apply to a case where the pollution intensity of the clean good production is strictly positive. See Levinson and Taylor, 2008 for a partial equilibrium example and Copeland and Taylor, 1994 for a general equilibrium discussion.

sector is a choice variable. The joint production of x and e is given by

$$x = B(K_x, L_x) - B(\phi K_x, \phi L_x)$$
$$= (1 - \phi)B(K_x, L_x) \tag{3.2}$$
$$e = \chi(\phi)\Omega B(K_x, L_x) \tag{3.3}$$

where the second line of equation 3.2 follows from the CRS assumption. $\chi(\phi)$ is the abatement function, with more abatement efforts leading to less emissions, i.e. $\frac{d\chi}{d\phi} < 0$, and $\chi(0) = 1; \chi(1) = 0$.[12]

In the absence of abatement ($\phi = 0, \chi(\phi) = 1$), each unit of good x produces Ω units of pollution; conversely, if all resources are devoted to abatement ($\phi = 1$, $\chi(\phi) = 0$), no production (nor pollution) takes place. $0 < \Omega \leq 1$ is therefore the unabated level of pollution attached to each unit of the dirty good and can be interpreted as a technological parameter for the abatement activity.[13] A decrease in Ω then denotes an improvement in the abatement technology (Brock and Taylor, 2010) and, for given levels of potential production and abatement effort, a decrease in emissions.

As shown in section 3.4.2, this parameter plays a central role in the determination of a jurisdiction's equilibrium emissions (i.e. climate policy). As a result, mechanisms leading to improvements in domestic abatement technology, which constitute one of the focal points of our discussion are particularly important.

To keep the discussion as focused as possible on this parameter, we note that, given equation 3.3, constraining the number of pollution units that the sector is allowed to release in the environment constrains its net production in the same way limited availability of an input would. Therefore, following Copeland and Taylor, 2003; Copeland and Taylor, 2004 we treat pollution as an input to the production process of good x and reformulate equation 3.2 accordingly. Under the assumption that $\chi(\phi) = (1 - \phi)^\alpha$, we can rewrite (3.2) as

$$x = \left(\frac{e}{\Omega}\right)^\alpha B(K_x, L_x)^{1-\alpha} \tag{3.4}$$

which expresses the net production of x as a function of *effective emissions*, e/Ω, i.e. emissions per emissions required for a unit of potential output, and potential output.

Proof. See appendix B.2. □

Equation 3.4 allows us to make three observations with important implications for domestic climate policy. First, it highlights once again the importance of the quality of the abatement technology: as emissions per unit of potential output (Ω) decrease, net output increases. This is because improvements in abatement technology free up resources that were previously

[12] As noted by Copeland and Taylor, 2003, adopting this specification is equivalent to assuming an explicit pollution abatement function. See appendix B.1.

[13] Restricting Ω to values below or equal to 1 ensures that emission intensity is below or equal to 1 and avoids unnecessary complexities in the firm's profit maximisation problem. In Copeland and Taylor, 2003, Ω is constant and, by choice of units, set equal to 1.

devoted to abatement and makes them available for actual production – see discussion in appendix B.2. In other words, for a given e, as the abatement technology improves, the production of the dirty good expands. Second, it can be shown that an improvement in abatement technology decreases the emissions intensity of the economy.[14] The third observation is summarised in the following proposition.

Proposition 1. *The effect on the net output of good x of a change in pollution emissions decreases in Ω. That is* $\left|\frac{\partial x}{\partial e}\Big|_{\Omega^{Low}}\right| > \left|\frac{\partial x}{\partial e}\Big|_{\Omega^{High}}\right|$.

Proof. The cost of tightening pollution policy in sector X is driven by the diversion of resources from actual production to abatement activities. From equation 3.4 it is easy to see how net output changes as a result of a change in allowed emissions:

$$\frac{\partial x}{\partial e} = \alpha \frac{e^{\alpha-1}}{\Omega^{\alpha}} B(K_x, L_x)^{1-\alpha} > 0 \tag{3.6}$$

which increases as Ω decreases. □

Although proposition 1 might appear counter-intuitive, it reflects the increased opportunity cost of reducing emissions when the economy is very efficient at abating, i.e. when the productivity of each unit of pollution (x/e) is high.

3.3.2 Production decision and pollution demand

Equipped with these technological priors, we now look at the production decision of firms.[15] This decision determines the relative size of the dirty sector and, ultimately, determines the pollution demand schedule, which will affect optimal climate policy.

Good y is the numeraire (with price p_y normalised to 1) and the relative price of good x in terms of good y is denoted p. The optimal output vector $\mathbf{t} = (x, y)$ will depend on primary input endowments, $\mathbf{r} = (K, L)$, output prices, $\mathbf{p} = (p, 1)$ and, for the pollution emitting sector, emissions e. That is, the firms' problem is

$$\max_{\mathbf{t}} \{\mathbf{p.t} \mid (t, r, e/\Omega) feasible\}$$

Since input factors (K,L) are supplied inelastically, the firms' decision determines the relative allocation of inputs to each sector. In the dirty good sector, the firm faces the additional decision

[14] This observation uses a standard implication of Cobb-Douglas production functions, i.e. that the share of payments in total value added to a factor of production is equal to the associated output elasticity parameter. That is

$$\frac{\delta \frac{e}{\Omega}}{px} = \alpha \Leftrightarrow i \equiv \frac{e}{x} = \frac{\alpha \Omega p}{\delta} \tag{3.5}$$

where δ is the price of emissions (see section 3.3.2) and p is the relative price of good x. Furthermore, equation 3.5 indicates that emission-intensity also depends on both policy (δ) and technology (Ω) – appendix B.4 discusses that relationship further.

[15] The detailed production decision problem of firms in sectors x and y is presented in appendix B.3.

of how much of these resources to devote to abatement. The solution to this problem defines the optimum (technologically feasible) vector of output

$$\hat{\mathbf{t}} \equiv t(\mathbf{p}, \mathbf{r}, e/\Omega) \tag{3.7}$$

Consequently, the (maximum) revenue function can be defined as

$$g\left(p, K, L, \frac{e}{\Omega}\right) = \mathbf{p}.t(\mathbf{p}, \mathbf{r}, e/\Omega) \tag{3.8}$$

The revenue function is convex in $\mathbf{p}$, $\bigtriangledown_{pp} g(\mathbf{p}, \mathbf{r}, e/\Omega) > 0$, but concave in $\mathbf{r}$, $\bigtriangledown_{rr} g(\mathbf{p}, \mathbf{r}, e/\Omega) < 0$.[16] In addition,

Proposition 2. *The revenue function is increasing and concave in e*

$$\partial g(\mathbf{p}, \mathbf{r}, e/\Omega)/\partial e > 0; \partial g(\mathbf{p}, \mathbf{r}, e/\Omega)/\partial^2 e < 0 \tag{a}$$

but decreasing and convex in Ω

$$\partial g(\mathbf{p}, \mathbf{r}, e/\Omega)/\partial \Omega < 0; \partial g(\mathbf{p}, \mathbf{r}, e/\Omega)/\partial^2 \Omega < 0 \tag{b}$$

That is, as the abatement technology deteriorates, revenue falls at a decreasing rate.

Proof. (a) The fact that the revenue function is increasing in e follows from Proposition 1 and the concavity of the revenue function in e can be justified following the same argument as for $\boldsymbol{r}$ – see Dixit and Norman, 1980, p.31. (b) With relative price $\boldsymbol{p}$ and total resources $\boldsymbol{r}$ held constant, a deterioration of the abatement technology will (i) induce a reallocation of resources from the dirty to the clean sector, as clean good production is now relatively more profitable – see equation B.3.4 in appendix B.3 – and (ii) reduce net output in the dirty sector – see equation 3.4. Similarly, convexity results from the the convexity in Ω of the production in the dirty sector. □

If we further assume that profit-maximising firms maximise national income, this revenue function can be interpreted as the *national income function*, $G(p, K, L, \frac{e}{\Omega})$.[17] Hence we write

$$I \equiv G\left(p, K, L, \frac{e}{\Omega}\right) = \max_{x,y} \left\{\mathbf{p} \cdot \mathbf{t} : \mathbf{t} \in T(K, L, \frac{e}{\Omega})\right\} \tag{3.9}$$

where I denotes the national income. The national income function preserves all the properties of the revenue function.

At this stage, it is useful to note the relationship between the national income function and the price of emissions. For given prices and factor endowments, the value of a pollution permit,

[16] For an informal justification of this statement, see Dixit and Norman, 1980, p.31.

[17] The assumption that profit-maximising firms in perfectly competitive environments maximise national income is a standard result in microeconomic theory which has been used extensively in the international trade literature. It holds as long as the negative environmental externality considered does not cause adverse production externalities. See Copeland and Taylor, 1994; Copeland and Taylor, 1995.

denoted δ, is the marginal effect on national income of additional pollution:

$$\delta \equiv \frac{\partial G(\mathbf{p}, \mathbf{r}, e/\Omega)}{\partial e} \tag{3.10}$$

Equation 3.10 gives the demand schedule of firms for pollution which, since $G(.)$ is concave in e, is decreasing. Hence, we also have

Proposition 3. *For a given net output of the dirty good sector, an improvement in the abatement technology reduces pollution demand. That is,* $\frac{\partial G(\mathbf{p},\mathbf{r},e/\Omega)}{\partial e \partial \Omega} > 0$

Proof. First, note from equation 3.5 that the demand for pollution can be expressed as the emissions intensity times the production of good x, i.e. $e = i(p, \delta, \Omega) \times x(p, \delta, K, L)$. Now, using equation 3.5 again, it is easy to note that an improvement in abatement technology (i.e. a decrease in Ω) leads to a decrease in emissions intensity – a *technique* effect. Hence, for a given level of production in the X sector, an improvement in abatement technology decreases demand for pollution. □

3.3.3 Consumers

Let us assume the existence of N identical consumers in each country. Consumers derive utility from the consumption of both goods and incur disutility – i.e. damage (D) – from global pollution E. The utility function is strongly separable with respect to consumption goods and environmental quality. Each consumer of jurisdiction i has the following utility[18]

$$U^i \equiv U^i(x, y, E) = u^i(x, y) - D(E) \tag{3.12}$$

where $E = \sum_i e_i$ and e_i denotes the emissions of jurisdiction i. $u^i_x(x, y), u^i_y(x, y) \geq 0, u^i_{xx}(x, y), u^i_{yy}(x, y) < 0$ and $D'(E) > 0, D''(E) > 0$. Note, in addition, that $u^i(x, y)$ is homothetic.[19] Consumers maximise utility given goods prices – which determine the revenue function specified by (3.8) – and (global) pollution levels. Using duality, we can write consumer i's indirect utility function, which gives the maximum utility attainable for given prices and income (I), as:

$$V^i \equiv V(\mathbf{p}, I, E) = v(\mathbf{p}, I) - D(E) \tag{3.13}$$

[18] Note that equation (3.12) assumes that the consumer does not derive any utility from global environmental quality. One could take this form of altruism into account by attributing a strictly positive weight to the damage that domestic emissions impose on other jurisdictions. That is, e.g.,

$$U^i \equiv U^i(x, y, E) = u^i(x, y) - [\alpha D_1(E)] + \beta D_2(E)] \tag{3.11}$$

where $\beta = 1 - \alpha < 1$ and D_1 and D_2 denote domestic and foreign (or world) environmental damage, respectively. Care for the global environment will reduce equilibrium emissions level.

[19] With homotheticity, the analysis is simplified in two ways. First, the indirect utility function can be written as an increasing function of real income. Second, it ensures that relative consumption patterns do not change with income which, in turn, makes trade patterns dependent on factor endowments and relative costs only (Copeland and Taylor, 2003).

Consumers earn their revenue from their ownership of factors of production, capital and labour, which are remunerated at the equilibrium market rate. In a perfectly competitive economy, the total value of payments to all factors of production is equal to the maximum value of production. It will thus depend on the composition of the economic production, the price at which said production is sold and environmental policy. Eventually, using the homotheticity assumption, function $v(.)$ can be written as a function of real income – $I/\omega(\mathbf{p})$, where $\omega(\mathbf{p})$ is a price index.

$$V^i(\mathbf{p}, I, E) = v(\mathbf{p}, I) - D(E) = v(1, I/\omega(\mathbf{p})) - D(E)$$

$$V^i(R, E) \equiv v(R) - D(E) \tag{3.14}$$

3.3.4 Equilibrium pollution supply

As alluded to in the introduction, climate policies developed over the last three decades have been so in an uncoordinated and non-cooperative fashion.We therefore consider a noncooperative Nash Equilibrium where pollution policy is endogenous and decided by a self-interested government, which maximises the utility of a representative consumer given world prices and Rest Of the World (ROW) emissions. Government policy is cast in terms of pollution targets, e_i. The problem of the government is as follows:

$$\max_{e_i} \quad V^i(R, E) \tag{3.15}$$

$$s.t.: \qquad R = [G(p, K, L, \frac{e_i}{\Omega})]/\omega(\mathbf{p}) \tag{3.16}$$

$$E = E_{-i} + e_i \tag{3.17}$$

where E_{-i} is the total aggregate emission of all jurisdictions bar the emissions of jurisdiction i. The optimality condition of this maximisation problem is:

$$\underbrace{V_R R_E}_{(1)} + \underbrace{V_R R_p p_e}_{(2)} + \underbrace{V_E}_{(3)} = 0 \tag{3.18}$$

Proof. To obtain equation 3.18 we acknowledge all the direct and indirect dependencies of V^i on domestic emissions e_i. First, domestic emissions affect the indirect utility via their impact on the national (real) income. They can affect the national income in two ways: (1) directly, by constraining the production of the dirty good – $\frac{e_i}{\Omega}$; (2) indirectly, by altering the relative price of the dirty good on world markets – $p(e)$. Second, domestic emissions affect the indirect utility via their impact on total emissions E. To see this more clearly, write

$$V^i(\underbrace{G(p(e), K, L, \frac{e_i}{\Omega})/\omega(\mathbf{p})}_{R}, \underbrace{E_{-i} + e_i}_{E}) \tag{3.19}$$

of which we take the total derivative with respect to e_i (given the presence of indirect dependencies of V on e_i and composed functions, we must resort to the chain rule). The total derivative is then written

$$\frac{dV}{dt} = \frac{\partial V}{\partial R}\frac{\partial R}{\partial p}\frac{dp}{de} + \frac{\partial V}{\partial R}\frac{\partial R}{\partial e_i} + \frac{\partial V}{\partial E}\frac{dE}{de_i} \tag{3.20}$$

If the domestic economy takes other jurisdictions' emissions as given, which is our default assumption, then $dE/de_i = 1$. Importantly, from the point of view of the domestic economy, this term captures free-riding and leakage issues. Indeed, if an economy's decision to reduce domestic emissions leads to less absolute reduction in world emissions, $dE/de_i < 1$, then domestic incentives to reduce emissions will decrease.

Next, defining $V_R \equiv \frac{\partial V}{\partial R}$, $R_p \equiv \frac{\partial R}{\partial p}$, $V_E \equiv \frac{\partial V}{\partial E}$, $p_e \equiv \frac{\partial p}{\partial e}$ and $V_E \equiv \frac{\partial V}{\partial E}$ yields the left hand side of equation 3.18.

Finally, note that V is a concave function because of the structure imposed on $u(.)$ earlier. Hence, setting equation 3.20 to 0 defines a maximum.

□

That is, the government's decision reflects the tradeoff between the direct effect of emissions change on the nation's real income (1), the effect of the induced change in the price of the dirty good on real income (2), and the effect of emissions change on the consumer's utility (3). However, if world prices are exogenous to domestic policy changes, (2) is equal to zero because there is no real income effect of a change in domestic prices. Hence,

$$R_E = \underbrace{-V_E/V_R}_{\equiv MD(R,E)} \tag{3.21}$$

with $V_E < 0$ and $V_R > 0$. Equation 3.21 equates the marginal benefit of increased emissions (i.e. the resulting increase in real income) to the domestic marginal damage of pollution and defines the optimal level of emissions e^*. Given that domestic consumers only account for domestic benefits of emissions abatement, this outcome is suboptimal from a global planner's perspective.

3.4 Diffusion mechanisms and (equilibrium) climate policy

We now return to our policy diffusion mechanisms to formally introduce them in the framework set up above and state our (empirical) hypotheses.

3.4.1 National income, free-riding and trade partners' climate policy

It emerges from the above non-cooperative framework that one of the primary concerns associated with (unilateral) climate policy strengthening in an open economy (i.e. tighter cap on emissions) relates to the associated loss in national income. In addition, if the economy is large relative to the size of the world market, increased emissions reduction might lead to significant free-riding by non-committed economies as well as 'carbon leakage' if its action induces a rise in the relative price of the dirty good (Copeland and Taylor, 2005).

3.4.1.1 National income

As mentioned earlier, we rule out the possibility that policy tightening by large net dirty good exporters may lead to a positive terms-of-trade effect. Although it is possible that some jurisdictions have indeed considered this effect, the record of climate policy development does not suggest that it has been sufficiently strong to induce significant emissions reduction.[20] Under this assumption, $p_e \equiv \frac{dp}{de_i} = 0$ and the income effect of domestic environmental policy tightening boils down to (1) in equation 3.18. It is therefore strictly negative.

Proposition 4. *For given world prices and ROW emissions, a marginal increase in domestic environmental policy stringency leads to a loss of real domestic income, R, of δ.*

Proof. This follows straightforwardly from equation 3.10 and results from the diversion of some domestic resources to abatement activity in the dirty good sector, which in turn reduces the net (optimal) supply by domestic producers and diverts some of the world demand to other world suppliers.[21] □

This result pertains to the domestic economic structure. Given that it is bears no relationship with decisions made by other countries and that domestic factors are investigated in chapter 2, it is not studied further, theoretically or empirically, in this chapter.

3.4.1.2 Free riding and carbon leakage

The income cost considered above would be the only concern of a single (small, relative to its trade partners) economy with no influence on relative world prices and whose emissions (as a share of the world total) would be too small to induce any significant free-riding.

A large economy (or a sufficiently large group of economies), however, would also account for the fact that its own (unilateral) emissions reduction might: (i) induce free riding on the part of other economies; (ii) lead to a change in the world price of the dirty good and induce carbon leakage. To see these latter effects formally, consider again $\frac{dE_{-i}}{de_i}$ and note that it can be decomposed as follows:

$$\frac{dE_{-i}}{de_i} = \underbrace{\frac{\partial E_{-i}}{\partial e_i}}_{(A)} + \underbrace{\frac{\partial E_{-i}}{\partial p}\frac{dp}{de_i}}_{(B)} \tag{3.22}$$

[20] Implications of the presence of international market power for pollution policy decision is considered by Lovely and Popp, 2011, in the context of SO_2 regulation. An extension of the present framework along similar lines could shed further light on climate policy adoption.

[21] Moreover, given the concavity in p of the national income function, the marginal value (in terms of national income) of a domestic unit of pollution increases with the price of the dirty good, which, under certain conditions, would further reduce incentives for unilateral action. Yet, Copeland and Taylor, 2005 showed that, in addition to the standard positive incentive to free-ride, a small economy's reaction to other jurisdictions' emissions reduction would depend on the substitution and income effects induced by a change in the relative price of the dirty good.

where (A) captures the pure free riding effect and (B) captures the leakage effect. The free-riding effect is negative, i.e. domestic emission reductions induce non-committed foreign jurisdictions to increase theirs. This effect induces higher equilibrium emissions or, equivalently, lower climate policy ambition. The leakage effect is typically assumed to be positive, i.e. a rise in the price of the dirty good induces non-committed jurisdictions to expand their dirty sector and to raise their own emissions.[22] These effects are particularly acute if the number of non-committed economies is large.

In practice, however, there is little ex-post evidence that carbon pricing and climate policies implemented so far have induced significant carbon leakage (see, e.g., Ward et al., 2015). Hence, we set (B) equal to 0 and focus on free-riding as the main channel of impact of domestic emissions on ROW emissions.

Proposition 5. *Reduced free-riding tightens the domestic abatement equilibrium.*

Proof. We denote foreign climate policy stringency by η and write $\left|\frac{\partial E_{-i}}{\partial e_i}|_{\eta^{high}}\right| < \left|\frac{\partial E_{-i}}{\partial e_i}|_{\eta^{low}}\right|$. That is, more stringent foreign climate policy strengthens the incentive for domestic policy strengthening. □

Much of the discussion around strengthening climate policy in relatively richer (and larger) economies has therefore focused on ways to avoid free riding (and carbon leakage), providing the motivation for calls to increase the number of economies committing to emissions reduction and, more specifically, increase the share of world GHG emissions covered by such commitments.

Prediction 1 The introduction of (more stringent) carbon pricing and other climate change mitigation policies by partner economies mitigates free-riding and induces more stringent domestic policy.

Unlike leakage, the free-riding problem occurs even if countries do not engage in international trade. In that respect, the extent of free-riding is only a function of the share of unconstrained world emissions. However, there is some evidence that countries care specifically about the (free-riding) behaviour of specific partners, e.g. trade partners (Sauquet, 2014). In particular, it suggests that commitment to reduce emissions by trade partners raises the probability of commitment by the domestic jurisdiction, i.e. that domestic and partner's commitment are strategic complements. Our empirical investigation in section 3.6 will test whether commitments by trade partners induces more stringent domestic policy by reducing the risk of free-riding.

3.4.2 Technological spillovers

As section 3.3.4 suggests – and as highlighted by integrated assessment modelling exercises (e.g. Kriegler et al., 2014), abatement technology – Ω – is a key determinant of the economy's

[22] Copeland and Taylor, 2005 show that leakage is not inevitable. See previous footnote.

(equilibrium) level of emissions. In particular, under certain conditions, an improvement in domestic abatement technology reduces equilibrium emissions. To see this, recall from the proof of proposition 3 that an improvement in abatement technology induces a *technique* effect and observe from appendix B.3 that it also induces a *composition* effect. For a given price of emissions, the former lowers total emissions in the dirty sector ($\frac{\partial G(\mathbf{p},\mathbf{r},e/\Omega)}{\partial e \partial \Omega} > 0$, see proposition 3) whereas the latter raises them. Hence the effect on equilibrium emissions will depend on the relative intensity of both effects.

Proposition 6. *Assuming that the composition effect is smaller than the technique effect, an improvement in abatement technology reduces equilibrium emissions as defined by equation 3.21.*

Proof. Formally, the technique and composition effects are apparent in $e = i(p, \delta, \Omega) \times x(p, \delta, K, L)$. Assuming that the decrease in emissions intensity (technique effect) more than outweighs the rise in dirty good production arising from the diversion of resources from the clean to the dirty sector (composition effect), an improvement in domestic abatement technology shifts the pollution demand schedule to the left and reduces total (equilibrium) emissions. □

Therefore, how this technology is developed and accumulated by a jurisdiction plays a significant role in the evolution of its CO_2 emissions and policy activity. One possibility for such accumulation is the spillover of foreign technological development (i.e. foreign jurisdictions' abatement technology stock) on domestic abatement technology (Bloom, Schankerman, and Van Reenen, 2013; Dechezlepretre and Glachant, 2011). These jurisdiction-specific spillovers, which we denote ψ are formally introduced in our model by assuming an explicit dependence of domestic abatement technology on them: $\Omega(\psi)$, with i.e. $\psi > 0$ and $\frac{\partial \Omega(.)}{\partial \psi} < 0$.

Prediction 2 Higher access/exposure to foreign abatement technology improves domestically available abatement technology, and strengthens the domestic abatement equilibrium.

In our empirical analysis, we follow Grossman and Helpman, 1991 and assume that the strength of the technology spillover effect is linked to bilateral trade relationships and that both import and export flows can affect domestic technology differently (Falvey, Foster, and Greenaway, 2004). Imports of intermediate goods embody foreign knowledge that is extracted by the recipient country and contributes to the domestic stock of (abatement) technology. This accumulation of technology might enhance home productivity, or prompt countries inside the technological frontier to imitate the products of frontier countries. For example, Lanjouw and Mody (1996) show that imported equipment is a major source of environmental technology for some countries. Exports, on the other hand, emphasise "learning-by-doing" and the "pure idea exchange and knowledge spillovers gained from formal and informal contacts"(Funk, 2001), which can encourage more efficient employment of resources or stimulate new indigenous technologies.[23]

3.4.3 Updated information

The third channel through which domestic policy ambition can be altered and considered in this paper is via an update on information about the cost of policy adoption. Substantial evidence indicates that governments often lack sufficient information to understand the political/societal cost of economic policy innovation (Simmons and Elkins, 2004) and/or expect the economic cost of implementation to be significant. In terms of climate policy this can represent the cost associated with the reallocation of resources from one industrial sector to another or the political cost of sustaining abatement policies (Mideksa, 2016).

Such perceived costs is likely to delay implementation of (more stringent) environmental policy. Therefore, a reduction in the expected (fixed) political or economic cost of regulation is likely to prompt more policy activity or increase policy stringency. In that respect, we understand policy makers as drawing information from two main sources: 1. past (foreign) policy experience; 2. (abatement) technology deployment and demonstration. First, early policy experience reveals information about the actual cost of implementation as well as institutional design features which can reduce them. For instance, at the international level, one can think of the EU-ETS as playing such role; at the sub-national level, California's ETS might be thought of playing a similar role with respect to other US States. Second, the proven availability (i.e. deployment and demonstration) of a (major) abatement technology provides information about the feasibility of deployment of specific technologies in the home jurisdiction.

To see this in a more formal way, we start by noting that the government's first decision (prior to choosing the emissions level) is whether or not to regulate and it will choose the option that maximises the representative consumer's utility. In the presence of regulation, pollution is chosen according to equation 3.21 and utility rises monotonically with income. In the no regulation case, the consumer faces ever increasing pollution which, assuming decreasing marginal utility of consumption and constant marginal disutility of pollution, implies that utility initially rises and ultimately declines with income – see appendix B.5. If the regulation is expected to require a fixed amount of primary inputs $(\bar{K}, \bar{L})$, regulatory activity will not occur until a threshold level of income, $\bar{I}$, above which the consumer's utility under regulation surpasses her utility under no regulation, is reached. Equivalently, a decrease in the expected regulatory cost reduces the income threshold at which policy activity is triggered. We define the expected regulatory cost as $\mathbb{E}(\bar{K}, \bar{L}) \equiv \Phi$ and formalise the above in the following proposition

[23] Competition in international markets might drive domestic exporters to acquire and adapt foreign technologies. Evidence of a 'trading up' effect, i.e. the fact that greater exports to jurisdictions with more stringent (environmental) regulations leads to a strengthening of domestic regulations, has been provided by Perkins and Neumayer, 2012 for the automotive industry.

Proposition 7. *A decrease in the expected fixed cost of regulation lowers the policy activity income threshold. That is,* $\partial \bar{I}/\partial \Phi > 0$.

Proof. See appendix B.5. □

This expectation, in turn, depends on accumulated foreign policy experience (α_i) as well as deployment and demonstration of abatement technologies (σ_i). Thus, we write $\Phi(\alpha_i, \sigma_i)$, with $\frac{\partial \Phi(\alpha_i,\sigma_i)}{\partial \alpha_i} < 0, \frac{\partial \Phi(\alpha_i,\sigma_i)}{\partial \sigma_i} < 0$. That is, as policy experience is accumulated and/or abatement technology is deployed, the expected fixed regulatory cost decreases.

Prediction 3 Policy implementation and technology deployment by (partner) jurisdictions reduces the expected fixed cost of regulation for the domestic economy which, in turn, increases both the probability of implementation and the stringency of (domestic) carbon pricing schemes.

While the altered payoffs mechanisms are intrinsically related to the relative strength of bilateral trade or financial flows (e.g. lump sum international transfers), the transmission of information across jurisdictions is tied to (potentially numerous) communication channels. With regard to these communication channels, previous literature considered (1) bilateral data (e.g. trade, number of telephone calls,. . .) and (2) affiliation data, e.g. membership of organisation, party to regional agreements,. . . (Simmons and Elkins, 2004) whereas cultural proximity is usually proxied by language or religious affiliations. This paper considers two channels. First, the policies of trade partners, as there is evidence that the strength of communication networks is correlated with bilateral trade relationships (Simmons and Elkins, 2004). Second, given that the EU as an organisation acts as a strong "coordination device" among its member states in several areas of public policy, involving repeated contacts between their respective civil servants, we suggest that information about climate policies may have been transmitted more easily between EU member states.[24]

3.4.4 Other (economic) channels

In addition to these mechanisms, policy stringency can also diffuse via non-economic channels. For example, Fankhauser, Gennaioli, and Collins, 2015 suggest that peer pressure can play a role in the international diffusion of policy (stringency); Frankel and Rose, 2005 further note that one may observe the international ratcheting of environmental standards: when a "significant" jurisdiction introduces more stringent environmental standards, others might follow suit. The legal literature on environmental policy refers to this effect as the 'California' effect (see, e.g., Vogel, 1995; Perkins and Neumayer, 2012). Though providing a different rationale for policy diffusion, these effects also relate closely to economic integration (the more integrated two economies are, the more likely they are to adopt each other's standards) and relative size (the relatively larger economy is more likely to be able to impose its standard).

[24]Note that such investigation could be repeated for other multilateral organisations such as the OECD.

It is plausible that other forms of (economic) relationships influence the international transfer of policy stringency. One possibility is Official Development Assistance; there is evidence, if only anecdotal, that several jurisdictions (e.g. Norway, the European Union) are taking relatively stringent emissions reductions commitment at home and are actively encouraging other jurisdictions to take steps towards climate change mitigation. Given the importance of extending climate policy regimes to all national jurisdictions in the world, especially nations whose emissions are currently growing under the combined effect of population and economic growth, it would be of significant interest to determine whether donor countries' policy stringency influence recipients' policy stringency.

TABLE 3.1: Main hypotheses

Category	Mechanism	Theoretical representation	Channel(s)	Data Source	Policy adoption	Policy stringency
Altered payoffs	Foreign abatement tech.	ψ_i	IM,EX	IMF, 2017	+	+
	Foreign policy stringency	η_i	IM,EX	IMF, 2017	n.a.	+
			ODA	OECD, 2016b	n.a.	+
Updated information	Policy demonstration	α_i	Cult. proximity	IMF, 2017	+/-	n.a.
			EU	Authors	+/-	n.a.
	Technology deployment	σ_i	Cult. proximity	IMF, 2017	+	+
			EU	Authors	+	+

3.5 Data and identification strategy

The empirical challenge ahead of us is now to (1) find appropriate proxies for the outcomes of interest (carbon pricing and other climate policies) as well as for the altered payoffs and informational update mechanisms that we identified; (2) evaluate their effect on policy developments, both adoption and stringency.

3.5.1 Policy developments

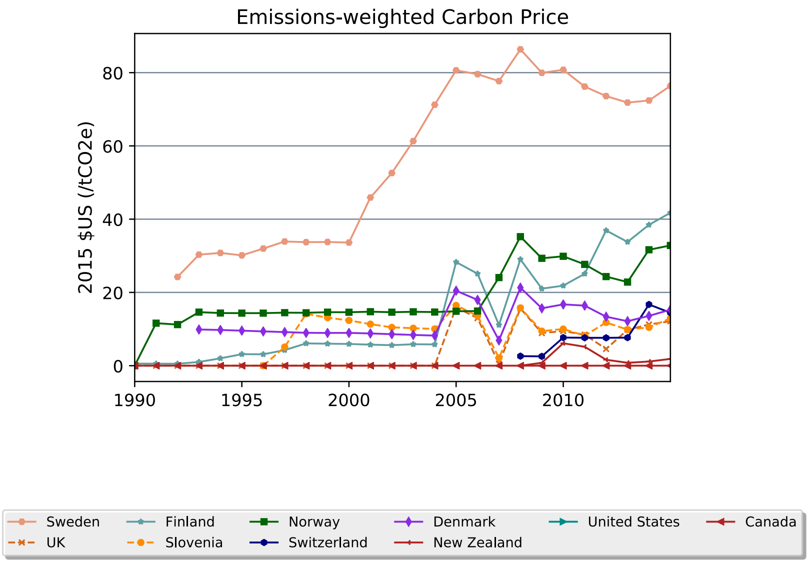
We analyse the adoption of both price and non-price climate change mitigation policies.[25] Since we investigate the dynamics of both policy adoption and stringency, policy developments within each jurisdiction are captured in two ways. First, a binary variable ($\mathbb{1}$) taking value 1 if a jurisdiction has adopted a given policy (in any sector of its economy) in a particular year, 0 otherwise.[26] Second, a variable capturing the stringency of the adopted policy. For carbon pricing policies, we use the Emissions-weighted Carbon Price (ECP) introduced in chapter 2 – see Figure 3.2a.[27] The proxy for non price climate change mitigation policies, constructed based on The GLOBE database, 2015, is the cumulative number of policies passed – see Figure 3.2b

[25]Looking at the latter group of policies is motivated by the fact that carbon pricing schemes are not the only policy tools that have been implemented to abate GHG emissions. In fact, these policies, however important, are still relatively marginal when considered in the context of all climate change mitigation policies adopted.

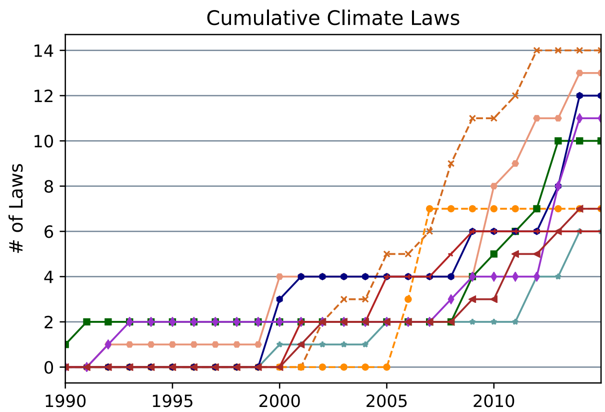
[26]This assumes that there are only two "policy states" possible and the "policy event", i.e. introduction of *a* climate change mitigation policy, occurs once.

[27]See appendix A for a description of the data collected and the methodology.

– in the following categories: Energy Demand, Energy Supply, Research and Development, Transport.



(A) Emissions-weighted carbon price – selected jurisdictions



(B) Cumulative climate laws – selected jurisdictions

FIGURE 3.2: Climate change mitigation policy stringency

3.5.2 Covariates

Now, identifying the source and strength of policy diffusion mechanisms requires that: (i) we construct variables (Λ) that capture changing payoff structures and new sources of relevant information; (ii) we identify the channels of diffusion, along with relevant proxies for the "distance" between (spatial) units. To account for (ii), we construct diffusion regressors that are defined as follows. For each jurisdiction i and year t, we can write

$$\Lambda_{i,t} \equiv \sum_{j \in \Theta_{i,t}} \Gamma_{i,j,t} x_{j,t}$$

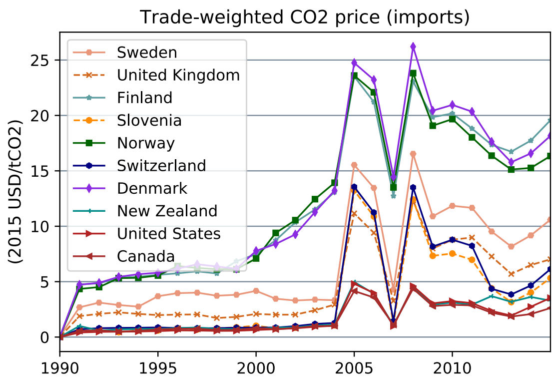
where $\Theta_{i,t}$ is the set of all partner jurisdictions of jurisdiction i in year t, $\Gamma_{i,j,t}$ is the partner-specific bilateral weight in year t, and x_j is the partner-specific value of variable x in that same year. The choice of the bilateral weights matrix depends on whether they constitute a proxy for a channel relevant to either the alteration of material payoffs or the transmission of information. The diffusion regressors are presented below.

Foreign climate policy stringency (η^{CL}, η^{ECP}) To account for (foreign) climate policy stringency, we use the ECP and the cumulative number of climate laws passed in partner jurisdictions. As noted in the formal discussion, the price of polluting emissions (whether explicit or not) relates directly to abatement efforts, i.e. the share of resources devoted to abatement. Since the response to more stringent foreign climate policy might differ depending on whether that stringency is raised by import or export partners, we distinguish between import and export channels.

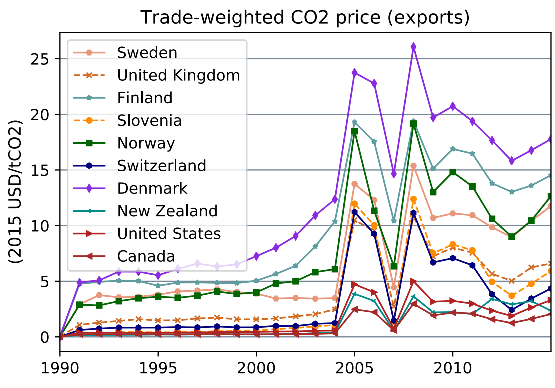
$$\eta^{CL}_{i,t}(IM) \equiv \sum_j \left[\frac{IM_{i,j,t}}{IM^{Tot}_{i,t}} \times CL_{j,t}\right] \qquad \eta^{CL}_{i,t}(EX) \equiv \sum_j \left[\frac{EX_{i,j,t}}{EX^{Tot}_{i,t}} \times CL_{j,t}\right]$$

$$\eta^{ECP}_{i,t}(IM) \equiv \sum_j \left[\frac{IM_{i,j,t}}{IM^{Tot}_{i,t}} \times ECP_{j,t}\right] \qquad \eta^{ECP}_{i,t}(EX) \equiv \sum_j \left[\frac{EX_{i,j,t}}{EX^{Tot}_{i,t}} \times ECP_{j,t}\right]$$

Figures 3.3 and 3.4 present this metric for selected jurisdictions. This sheds light on the *external* effect of CO_2 pricing and the significant role played by the EU-ETS for non EU-ETS jurisdictions.



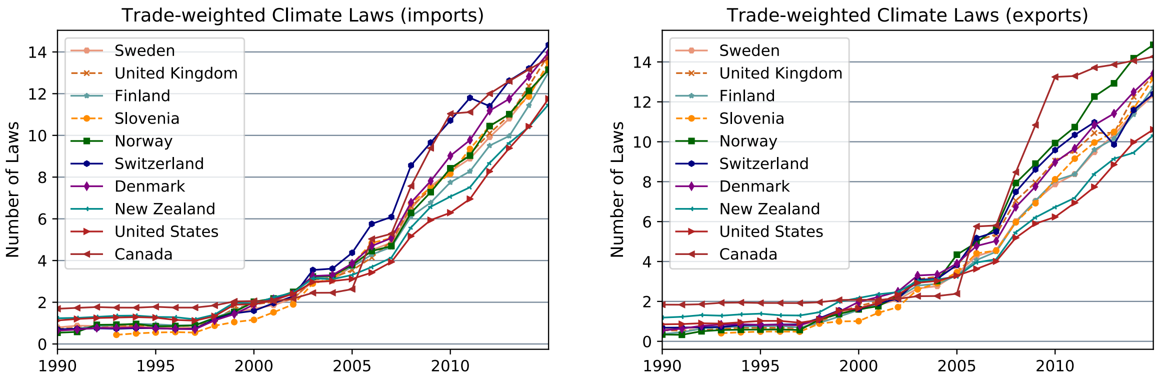
(A)



(B)

FIGURE 3.3: CO_2 pricing schemes of import and export partners

Abatement technology spillovers (ψ) The stock of abatement technology (in partner jurisdictions) is captured by the cumulative count of *climate change mitigation* technology patents since 1985 ($\bar{\kappa}$). This approach builds on the literature suggesting the use of patent data as proxy for



(A) (B)

FIGURE 3.4: Cumulative climate policies of import and export partners

the output of the innovation process (Griliches, 1990) and has been used in recent studies looking at the diffusion of climate change mitigation technologies (e.g. Dechezlepretre, Glachant, and Meniere, 2013).

In line with our theoretical discussion in section 3.4.2, the technology diffusion regressor is then defined, for each country-year, as the import- or export-weighted aggregate of all abatement technology stock from trading partners – Figure 3.5.[28] The import-weighted measure captures the embodied technology assumption whereas the export-weighted metrics emphasise the pure exchange of ideas.

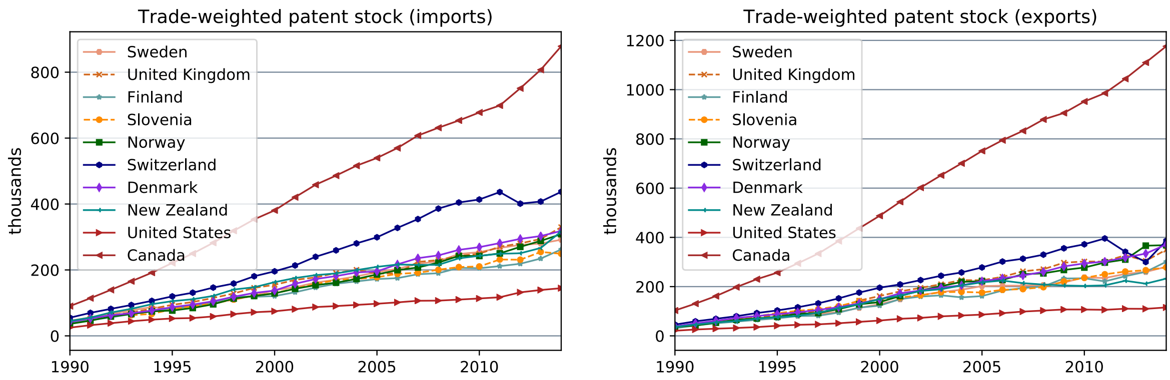
$$\psi_{i,t}(IM) \equiv \sum_j \left[\frac{IM_{t,j,i}}{IM_{i,t}^{Tot}} \times \bar{\kappa}_{j,t} \right] \qquad \psi_{i,t}(EX) \equiv \sum_j \left[\frac{EX_{t,j,i}}{EX_{i,t}^{Tot}} \times \bar{\kappa}_{j,t} \right]$$

Policy learning (α^{CL}, α^{P}) The informational signal that each jurisdiction sends by implementing climate policies is captured by two variables: the number of partner jurisdictions having adopted at least one non-price climate policy or adopted a carbon pricing scheme (either a carbon tax or trading system).[29] The proxy for the aggregate signal received from all partner jurisdictions is then:

- the weighted average of all partner specific signals received where the weights are the share of each partner j's total trade with jurisdiction i in that jurisdiction's total trade

[28] This assumes that technology diffusion is not only a trade-related phenomenon but is also local in nature. It might be argued that what matters is a global technological pool, in which case technology development data aggregated at the world level would be sufficient. In addition, note that this proxy relies on the assumption that a positive correlation exists between aggregate trade flows and those for climate change mitigation technologies.

[29] Policy adoption is interpreted as a sign of successful implementation.



(A) (B)

FIGURE 3.5: Climate change mitigation technological stock of import and export partners

flows

$$\alpha^{CL}_{i,t}(IM+EX) \equiv \sum_j \left[\frac{(IM+EX)_{j,t,i}}{(IM+EX)^{Tot}_i} \times CL_{j,t}\right]$$

$$\alpha^{P}_{i,t}(IM+EX) \equiv \sum_j \left[\frac{(IM+EX)_{j,t,i}}{(IM+EX)^{Tot}_i} \times P_{j,t}\right]$$

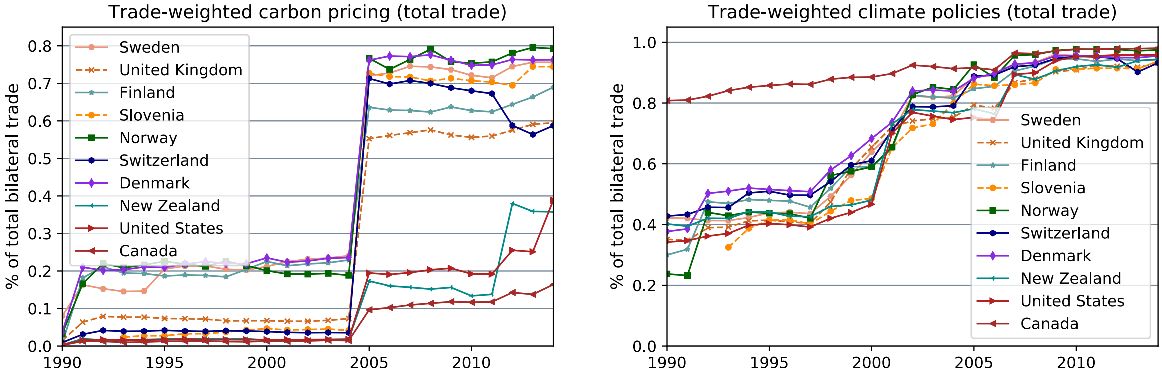
In weighting the received signal by total bilateral (trade) relationship, we assume that the strength of the signal is related to the total bilateral relationship, which follows earlier literature (Simmons and Elkins, 2004). As can be observed on Figure 3.6, little climate-related legislative activity takes place before the late 1990s. Moreover, it is interesting to note that even countries that did not implement carbon pricing or other climate change mitigation policies domestically are “exposed" to it (see, for example, Canada and the United States).

- the sum count across partners affiliated to the same organisation, in this case the EU. To this end, we construct dyadic matrix recording affiliation to the same organisation (the EU) for each pair of countries in the sample in any given year between 1990 and 2014.

$$\alpha^{CL}_{i,t}(EU) \equiv \sum_j \left[EU_{i,j,t} \times CL_{j,t}\right] \qquad \alpha^{P}_{i,t}(EU) \equiv \sum_j \left[EU_{i,j,t} \times P_{j,t}\right]$$

where $EU_{i,j,t}$ takes value 1 if both countries i and j are part of the EU in year t.

Technology demonstration (σ) Finally, our proxy for foreign abatement technology deployment and demonstration is the cumulative installed electricity generation capacity from wind



(A) (B)

FIGURE 3.6: Climate policies of trade partners (total bilateral trade)

and solar energy (RE).[30] Increased cumulative installed capacity provides evidence of an existing (and proven) alternative to fossil-fuel based electricity generation capacity.[31] As for the policy learning effect, the signal derived from technology demonstration is modelled as relating to either

- the strength of the total bilateral (trade) relationship

$$\sigma_{i,t}(IM+EX) \equiv \sum_j \left[\frac{(IM+EX)_{j,t,i}}{(IM+EX)_i^{Tot}} \times RE_{j,t} \right]$$

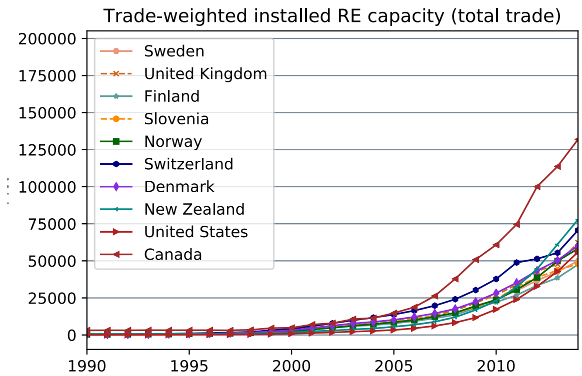


FIGURE 3.7: Installed renewable electricity generation capacity of trade partners

[30]This *de facto* restricts our attention to the power sector. However, given that it is one of the first economic to have been subject to decarbonisation efforts across almost all jurisdictions, it is safe to consider that it is representative of the technologies relevant to climate policy making so far.

[31]Increased cumulative installed capacity also has implications for technology learning. In terms of development/diffusion, additional installed capacity increases the stock of technology from which other jurisdictions can learn and contributes to the reduction of the (unit) cost of the technology through 'learning by doing' (Arrow, 1962b). In the case of solar photovoltaics, for example, IRENA, 2012 finds that costs decline by 22% for every doubling of capacity.

- EU membership, using the same dyadic matrix as before.

$$\sigma_{i,t}(EU) \equiv \sum_j [EU_{i,j,t} \times RE_{j,t}]$$

Official Development Assistance To gauge whether bilateral development assistance is used to prompt recipient jurisdictions to introduce climate change mitigation legislation, we construct a proxy for partner jurisdictions' policy stringency where the bilateral weights are the bilateral shares of Official Development Assistance (ODA) between recipient and donor countries. The effect of this variable is tested on the stringency of non price climate change mitigation policies rather than carbon pricing legislation because carbon pricing schemes have been introduced mainly among OECD countries. As before, this stringency is proxied as the cumulative number of climate laws passed.

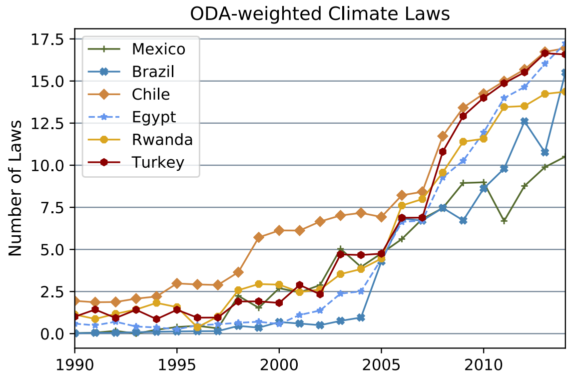


FIGURE 3.8: Climate policies of Official Development Assistance donors

Control mechanisms In discussing the diffusion of policies across jurisdictions, it is important to control for domestic (political and economic) conditions that could influence a jurisdiction's adoption of policies (Volden, Ting, and Carpenter, 2008). This, because the observed adoption outcome(s) could also reflect the fact that similar jurisdictions respond similarly – yet independently – to the same issue. To control for these we use GDP per capita (PPP, thousand constant 2011 USD), an indicator of Democracy, and the degree of openness as proxied by the ratio of total trade over GDP. GDP per capita captures the standard income effect and, assuming that environmental quality is a normal good, should have a positive impact on both policy adoption and stringency.

3.5.3 Modelling approach

The analysis is performed on a dataset covering 109 national jurisdictions over the period 1990-2014.[32] We thus have (a maximum of) 2725 country-year observations. The modelling approach

[32]The panel dimension of our dataset is limited by the data on the level of democracy whereas the time dimension is constrained by the availability of patent data from the OECD.

TABLE 3.2: Variables' sources and summary statistics

Category	Variable	Source	Weight	Mean	Std. Dev.	Min.	Max.	N
Outcome - adoption	Pricing	Author created	-	0.12	0.33	0	1	2725
	Climate Law	Author created	-	0.46	0.5	0	1	2725
Outcome - stringency	ECP(2013)	Author calculations	-	1.68	7.65	0	95.21	2725
	Cum. Climate Law	Author calculations	-	2.39	3.67	0	21	2725
Technology stock	Patent stock	OECD, 2019	IM	79.14	58.2	2.45	439.34	2635
	– thousands		EX	93.255	81.93	0.05	630.45	2635
Foreign stringency	Carbon Price	Author's data	IM	2.44	3.36	0.002	26.2	2635
			EX	2.25	3.24	0.002	26.06	2635
	Climate Laws	Author's data	IM	3.69	3.39	0.03	14.1	2635
			EX	3.76	3.55	0	14.21	2635
			ODA	4.88	4.66	0	17.62	1263
Policy learning	Foreign Pricing	Author's data	IM+EX	0.16	0.22	0	0.83	2635
			EU	1.97	6.39	0	25	2700
	Climate Law	GLOBE database, 2018	IM+EX	0.64	0.25	0.02	1	2635
			EU	1.79	5.01	0	19	2700
Tech. demonstration	RE capacity	United Nations, 2018	IM+EX	6.44	9.89	0	82.79	2635
	– GW		EU	8.97	33.36	0	217.08	2700
Control	Democracy	Varieties of Democracy, 2018	-	0.46	0.28	0.014	0.903	2715
	GDP per cap.	World Bank, 2016a	-	16.46	17.04	0.35	111.07	2687
	Trade openness	World Bank, 2016a	-	78.37	44.68	0.02	441.6	2645

adopted is different for the policy adoption decision and the policy stringency.

Adoption The literature on policy adoption usually investigates such questions with event history or hazard models. Berry and Berry, 1990 use a panel probit approach, observing the evolution of lottery adoption over the period 1964-1986 in 48 US States. Simmons and Elkins, 2004 model the adoption of liberal economic policies as a transition between two (mutually exclusive) states using a Weibull survival model. In these latter analyses, all units "enter" the sample in a – somewhat arbitrarily – determined year from which jurisdictions are "at risk" of adopting the policy and "leave" as soon as a failure (i.e. policy adoption) occurs. When looking at the adoption of domestic environmental policies, several international agreements in which these jurisdictions have taken binding commitments could be used as starting year. This is the approach taken in Fredriksson and Gaston, 2000 to analyse the ratification of the UNFCCC by national jurisdictions following its signature in 1992. However, since the first carbon pricing scheme was adopted before any international legally binding agreement, we follow Berry and Berry, 1990 and take the year of introduction of the first carbon pricing scheme, 1990, as our starting point. That is, every country enters the dataset in 1990 and the last observation recorded for each unit is the year in which the adoption of a given policy (either carbon pricing or the first 'non pricing' policy) occurred. Formally, we have:

$$\mathbb{1}_{i,t} = \boldsymbol{\beta} \boldsymbol{X}_{i,t-1} + \boldsymbol{\lambda} \boldsymbol{W}_{i,t-1} + \boldsymbol{\gamma} \boldsymbol{C}_{i,t} + d_t + \epsilon_{i,t} \tag{3.1}$$

where $\mathbb{1}_{i,t}$ denotes the presence (1) or absence (0) of a carbon pricing scheme in any sector of jurisdiction i in year t, $\boldsymbol{X}$ is the set of variables capturing the changes in net payoffs, $\boldsymbol{W}$ includes the variables capturing policy learning, $\boldsymbol{C}$ is the set of 'control' variables; d_t is the vector of time dummy variables; β, λ and γ are vectors of dimensions m, n and p, respectively, each element of which corresponds to the estimated parameter of the associated explanatory variable. ϵ_{it} is the observation specific error term.

Stringency Because the stringency of carbon pricing policies is not measured in the same way as that of other climate policies – the former is a continuous variable whereas the latter is a non-negative discrete variable – we model these two outcome variables differently. The ECP is modelled as a standard linear process

$$ECP_{i,t} = \boldsymbol{\beta X}_{i,t-1} + \boldsymbol{\lambda W}_{i,t-1} + \boldsymbol{\gamma C}_{i,t} + \phi_i + d_t + u_{i,t} \tag{3.2}$$

where $ECP_{i,t}$ is the emissions-weighted average carbon price in jurisdiction i at time t and ϕ_i is the unobserved jurisdiction fixed-effect; u_{it} is the observation specific error term. The modelling approach used for non pricing climate policies follows that adopted in Fankhauser, Gennaioli, and Collins, 2015, i.e. a negative binomial fixed-effects model.

$$CL_{i,t} = \boldsymbol{\beta X}_{i,t-1} + \boldsymbol{\lambda W}_{i,t-1} + \boldsymbol{\gamma C}_{i,t} + \phi_i + d_t + u_{i,t} \tag{3.3}$$

Unlike the adoption equation, equations (3.2) and (3.3) are estimated on the full data sample, running from 1990 to 2014. In all equations, all covariates except the 'control' variables enter the model with a one year lag to reflect the fact that it takes time for policy and/or technology developments in partner jurisdictions to "diffuse" to the domestic jurisdiction and then translate into policy decisions.

3.6 Results

3.6.1 Adoption

The results in table 3.3 show that policy adoption, either carbon pricing or other, is related to past adoption of the same policy in geographically and/or culturally close partner jurisdictions. This is consistent with our third hypothesis and suggests that free riding on other jurisdictions' climate change mitigation policy initiatives is not a strong driver of domestic climate policy activity. This effect seems to be of a larger magnitude for carbon pricing schemes – estimations (1) and (2) – than for non price climate policies – estimations (3) and (4). Interestingly, the effect of an EU-related information transmission channel is only confirmed for carbon pricing policies, not for non price climate policies. Overall, this provides some support for our *policy learning* hypothesis and emphasises the potential for (a group of) jurisdictions to demonstrate the feasibility of specific policy innovations but casts doubt on the idea that the EU served as a key information transmission channel, especially for non price climate policies. Similarly, the deployment of renewable electricity generation capacity, which we assumed carries information about the availability of an abatement technology, relates positively to the adoption of carbon pricing and other climate policies when weighted by the total bilateral trade relationship but not when weighted by the EU. The magnitude of the associated coefficient is larger for non price policies than for carbon pricing policies – except in estimation (2), where it is an order of magnitude larger for pricing policies. It must also be noted that, although the estimated coefficient might seem quite small, trade-weighted installed RE capacity is measured in GW and the maximum is 165.57 GW. Finally, the results for our proxy of the stock of climate change mitigation technologies does not allow us to confirm that an increase in the stock of such technologies in partner jurisdictions fosters policy adoption. Hypothesis 1 remains therefore unverified and would require further investigation.

GDP per capita and the level of democracy both affect positively the probability of adoption of price and non price policies, although the effect of the former is found to be meaningfully positive in estimation (1) only. It is unsurprising that these characteristics are found to have a stronger impact on the implementation of carbon pricing policies since these policies have been introduced among richer countries whereas other climate change mitigation policies have been introduced by relatively less well off jurisdictions. Lastly, we note the negative values of the estimated intercept parameter across all estimations, indicating that in the absence of the (positive) effect of our covariates, the probability of adoption of the policies under investigation is very low.

TABLE 3.3: Policy adoption

Category	Variable	Carbon Pricing		Climate Policy	
		(1)	(2)	(3)	(4)
Technology diffusion	$\psi(\text{IM})_{t-1}$	$-6.59e^{-7}$	$-1.98e^{-5}$	$7.71e^{-7}$	$1.85e^{-6}$
		$(1.72e^{-6})$	(1.69^{-5})	(1.24^{-6})	(2.49^{-6})
	$\psi(\text{EX})_{t-1}$	$6.59e^{-8}$	$4.47e^{-6}$	2.32^{-7}	5.51^{-7}
		$(1.15e^{-6})$	(1.01^{-5})	(6.73^{-7})	(1.36^{-6})
Policy learning	$\alpha^P(\text{IM+EX})_{t-1}$	1.68^{***}	11.21^{***}		
		(0.52)	(3.866)		
	$\alpha^P(\text{EU})_{t-1}$		1.89^{***}		
			(0.653)		
	$\alpha^{CL}(\text{IM+EX})_{t-1}$			0.78^{*}	0.73^{*}
				(0.41)	(0.421)
	$\alpha^{CL}(\text{EU})_{t-1}$				0.08
					(0.056)
Tech demonstration	$\sigma\ (\text{IM+EX})_{t-1}$	$1.27e^{-2*}$	$1.92e^{-1**}$	$3.27e^{-2***}$	$6.61e^{-2***}$
		$(6.84e^{-3})$	$(7.55e^{-2})$	$(1.1e^{-2})$	$(2.21e^{-2})$
	$\sigma\ (\text{EU})_{t-1}$		$2.66e^{-2}$		$-1.9e^{-2}$
			$(5.86e^{-2})$		$(2.17e^{-2})$
Control(s)	GDP per cap.	0.017^{***}	0.08	0.0002	-0.002
		(0.006)	(0.054)	(0.005)	(0.005)
	Trade openness	0.002	0.01	0.003^{*}	0.003
		(0.002)	(0.014)	(0.002)	(0.002)
	Democracy	2.99^{***}	12.72^{**}	0.44^{*}	0.35
		(0.68)	(5.014)	(0.242)	(0.257)
	Constant	-5^{***}	-20.98^{***}	-2.52^{***}	-2.49^{***}
		(0.59)	(5.995)	(0.236)	(0.244)
	Year FE	No	No	No	No
	Observations	2165	2141	1200	1197

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

3.6.2 Stringency

The results in table 3.4 – estimation (5) – indicate that the stringency of carbon pricing policies was, over the sample period, mainly driven by the past average price in other jurisdictions. This effect is present regardless of whether the variable is weighted by imports or exports, suggesting that countries with a carbon price are closely integrated through trade. We nonetheless note that the magnitude of this effect is about 1.5 times larger for imports than exports, More precisely, an increase of \$1/tCO_2e in the import-weighted (export-weighted) average price of emissions is associated with an increase of \$0.29/tCO_2e (\$0.21/tCO_2e) in the domestic average price of carbon. This effect is most likely driven by EU jurisdictions, which have implemented a common carbon pricing scheme in 2005 but were, and still are, closely (trade-)integrated. Interestingly, the stringency of foreign carbon pricing schemes seems to affect both the stringency of domestic price and non-price climate change mitigation policies. However, as far as the stringency of non price climate policies is concerned, the direction of the previous effect depends on whether stringency is increased in import partners (-) or export partners (+), giving some grounds to the existence of a potential free riding on other jurisdictions' mitigation efforts effect. However, the stringency of non price climate policies (whether weighted by imports or exports) does relate positively to domestic non price climate policy stringency.

The deployment of renewable energy electricity generation capacity, which we interpreted as providing information about the availability and feasibility of domestic deployment of an abatement technology relates positively to the stringency of carbon pricing policies, be it weighted by the strength of the bilateral relationship or by affiliation to the European Union. For example, a 100GW increase in the weighted stock of RE installed capacity would, on average, induce a \$7.6/tCO_2e increase in the stringency of carbon pricing policies – estimation (5). The development of abatement technology (as measured by the patent stock) does, however, relate negatively to the stringency of both price and non-price climate policies, although the estimated effect is only statistically significant in estimation (6) and only for the import-weighted variable.

The results also suggest that Official Development Assistance and the associated relationships constitute a significant driver of domestic policy stringency for recipients of ODA – estimation (7). Indeed, results indicate that an increase in the cumulated legislative activity in donor countries results in increased stringency in receiving countries. Given the way the proxy is constructed it is not possible to say whether this effect is driven by particular donor countries but it could constitute an interesting extension of the present work. Moreover, the coefficient on the import-weighted foreign non-price climate policy stringency suggests that recipients of ODA would, on average, lower the stringency of their own non price climate policy regime in response to an increase in the stringency in their import markets.

Finally, income per capita and trade openness increase the price of carbon by, on average, \$0.14/tCO_2e and \$0.004/tCO_2e respectively. No effect of these variables is detected on the stringency of non price climate policies, except in the case of receivers of ODA. For these countries, GDP per capita and trade openness positively affect the domestic stringency of non price climate policies.

TABLE 3.4: Policy stringency

Category	Variable	ECP	Climate policies	
		(5)	(6)	(7)
Technology diffusion	$\psi(\text{IM})_{t-1}$	$-1.75e^{-6}$	$-1.70e^{-6***}$	
		($4.65e^{-6}$)	$5.61e^{-7}$	
	$\psi(\text{EX})_{t-1}$	$-3.23e^{-6}$	$-6.72e^{-8}$	
		($2.79e^{-6}$)	$3.95e^{-7}$	
Foreign policy stringency	$\eta^{ECP}(\text{IM})_{t-1}$	0.29***	-0.05***	0.05
		(0.079)	(0.018)	(0.047)
	$\eta^{ECP}(\text{EX})_{t-1}$	0.21***	0.05***	-0.03
		(0.079)	(0.018)	(0.034)
	$\eta^{CL}(\text{IM})_{t-1}$	0.17	0.05*	-0.19***
		(0.15)	(0.032)	(0.042)
	$\eta^{CL}(\text{EX})_{t-1}$	-0.20	0.06**	0.05
		(0.126)	(0.028)	(0.038)
	$^{CL}(\text{ODA})_{t-1}$			0.04**
				(0.016)
Tech demonstration	$\sigma(\text{IM+EX})_{t-1}$	$7.46e^{-2**}$	$-4.01e^{-3}$	$-1.23e^{-2}$
		($3.22e^{-2}$)	($5.45e^{-3}$)	($7.56e^{-3}$)
	$\sigma(\text{EU})_{t-1}$	$4.13e^{-2***}$	$-1.56e^{-3***}$	
		($3.4e^{-3}$)	($5.71e^{-4}$)	
Control(s)	GDP per cap.	0.14***	-0.01	0.05*
		(0.025)	(0.001)	(0.029)
	Trade openness	0.004	-0.0004	0.006**
		(0.005)	(0.001)	(0.003)
	Democracy	-0.25	0.32	0.83
		(1.045)	(0.351)	(0.6)
	Constant	-1.36***	0.46	11.98
		(0.736)	(0.479)	(292.221)
	Year FE	Yes	Yes	Yes
	Observations	2438	2390	1068
	R^2	0.23	-	-

3.6.3 Summary and discussion

The analysis conducted above sought to shed light on potential channels of climate policy diffusion and assess their empirical relevance. The results presented provide support for some of the suggested channels. In particular, we find evidence that policy adoption by foreign jurisdictions positively affects domestic policy adoption. This is in line with Fankhauser, Gennaioli, and Collins, 2015. However, we confirm that this diffusion effect may be more subtle than one might have assumed so far. The analysis indeed shows that two diffusion channels were particularly important. First, in our sample, climate policies diffused primarily to culturally close neighbours (as proxied by total bilateral trade). Second, while carbon pricing policies have clearly diffused among a very specific group of countries, i.e. EU member states, it is not clear that this has been the case for non price climate policies.

Second, our results also suggest that technology demonstration played a role in policy adoption. This effect, which has not been discussed in earlier literature, bears particularly strong implications for the adoption of future (potentially sector-specific) climate policies. Indeed, it indicates that the demonstration of particular abatement technologies at scale can not only foster their adoption directly but also favour the adoption of (more stringent) climate policies which, in turn, could trigger a higher uptake of the technology. A clearer understanding of such effects could be gained by extending the analysis to specific technologies and associated policies. In a world that is seeking to avoid dangerous climate change, this seems a legitimate avenue to explore.

Third, the analysis provides interesting insights for the diffusion of (non-price) climate policies to recipients of Official Development Aid. Indeed, it seems that there is a positive relationship between donors and recipients' respective policy stringency. At this stage, we are only establishing the potential existence of such a relationship but are not making any claim as to the exact nature of the channel, a question which deserves further attention. On the other hand, the analysis did not confirm the role of foreign technology development for either domestic climate policy adoption or stringency. Such a result may be due to: (i) the genuine absence of such a relationship; (ii) inadequacy of our empirical proxy. Indeed, the proxy we constructed relies on the assumption that foreign technological development spills over to the domestic jurisdiction and contributes to the improvement of its own abatement technology stock. As we alluded to earlier, it may be the case that the transfer of climate change mitigation technologies follows different channels than bilateral trade networks. If this is the case, investigating the issue with the proxy used in Dechezlepretre, Glachant, and Meniere, 2013, i.e. the number of patents filed in country j by inventors from country i, and constructed based on EPO Worldwide Patent Statistical database could provide a better proxy.

TABLE 3.5: Results summary

Category	Mechanism	Theoretical representation	Channel(s)	Policy adoption	Policy stringency
Altered payoffs	Foreign abatement tech.	ψ_i	IM	/	/
			EX	/	/
	Foreign stringency	η_i	IM	n.a.	+
			EX	n.a.	+
			ODA	n.a.	+
Updated information	Policy demonstration	α_i	Cult. proximity	+	n.a.
			EU	+	n.a.
	Technology deployment	σ_i	Cult. proximity	+	+
			EU	+	+

Fourth, it is worth recalling that the theoretical analysis and empirical discussions here are conducted under the assumption of constant returns to scale in both abatement and production. In the context of our model, constant returns to scale in abatement imply that emissions will only fall if climate policy is tightened. Assuming increasing returns to scale would introduce efficiencies related to the scale of operation, which would make abatement more profitable even with unchanged policy (Copeland and Taylor, 2003). Such effects are currently not accounted for in our theoretical framework and not tested empirically.

In addition, it is clear that our focus on constant returns to scale in both the dirty and clean productive sectors prevents us from considering cases where these sectors are monopolistically competitive. Considering a departure from constant returns to scale in production would uncover additional insights with regard to the sectors' response to both tighter climate policy and changes in the international environment. Ultimately, this could lead to more detailed understanding of optimal policy formation and policy diffusion mechanisms.

Finally, the specifications presented above only include GDP per capita and a proxy for Democracy (Polity IV) as covariates capturing the level of development and the quality of institutions. Yet, the sample includes countries with very heterogeneous levels of development and institutional quality, and which vary along dimensions that are not necessarily captured by (or correlated with) GDP per capita and the Polity IV index. Hence, inclusion of such variables could provide more subtle evidence as to the role played by institutions.

3.7 Conclusion

The last quarter century has witnessed the development of a significant number of carbon pricing and climate change mitigation policies. This chapter holds that these developments are partly the result of a process of policy diffusion, which rests on (i) the transfer of abatement technology; (ii) technology and policy demonstration effects. It emphasises the importance of bilateral relationships for the implementation of domestic environmental policies, providing a new perspective on the emergence of bottom-up climate "coalitions" and the role that international institutional 'architecture' may play in it. Relatedly, it also suggests that we might have to revisit our assessment of the multilateral approach to climate change mitigation. Indeed, although we must be disappointed when international environmental agreements set lenient targets, there is a possibility that their very existence and architecture fosters the bilateral exchange of policy ideas and/or abatement technologies which, in turn, would increase the "unilateral" ambition of jurisdictions. In that respect, we believe that the European experience holds particularly strong insights for future carbon pricing developments. Indeed, integration, be it through trade or broader institutional arrangements, seems to foster policy diffusion by enhancing access to technological advances within the integrated group and strengthening the policy signal.

From a policy perspective, these results are particularly important as they cast a new light on the external effects of (unilateral) domestic carbon pricing – and climate change mitigation – policy developments. In particular, in contrast to some of the results in the *top down* environmental coalition formation literature, they suggest that convincing "key" countries to adopt tighter climate change mitigation policy frameworks might matter for the (simultaneous or sequential) policy strengthening by other jurisdictions. For example, the implications (in terms of policy diffusion and strengthening) of China adopting a more stringent policy regime may well be much more significant than that of a similar action by, e.g. Vietnam.

In a world where globally coordinated action has failed to deliver environmentally efficient outcomes, we must find a deeper understanding of the external effects of unilateral policy development.

Chapter 4

Identifying innovative actors in the Electricity Supply Industry using machine learning: an application to UK patent data

4.1 Introduction

Over the course of the last thirty years, the Electricity Supply Industry (ESI) of several OECD economies experienced significant structural changes (International Energy Agency, 2000; Nicolli and Vona, 2019). These changes occurred against the backdrop – and under the impulse – of two pivotal policy developments. First, the liberalisation of their respective electricity sector, which initiated a transition from vertical integration to unbundling of electricity supply activities (generation, transmission and distribution) and the introduction of wholesale competition.[1] Second, the development of increasingly stringent power sector decarbonisation policies, which at times came to co-exist with liberalisation agendas.

Liberalisation – and ensuing structural reorganisation of the ESI – had a significant impact on the innovation activity of its actors for several reasons. First, liberalisation of downstream stages of the ESI affected incentives to innovate of both downstream actors and upstream Original Equipment Manufacturers (OEMs).[2] Second, liberalisation changed the identity of downstream actors, from government-owned vertically integrated entities (and associated research centres) to private competitive firms, and hence altered the nature of the incentives their innovation activity is sensitive to. Third, these changes were often accompanied by a restructuring of public energy R&D institutions and a reduction in associated spending. In the UK, public spending on energy R&D (all technologies) decreased consistently between 1985 and 1999, only recovering from 2003 onward with increased funding directed at renewable electricity generation technologies. Finally, these regulatory changes occurred during – and allowed for – a

[1] This process was first initiated in the UK (Electricity Act 1989) and the US (1992 Energy Policy Act), and subsequently in the European Union (Directives 96/92/EC, 2003/54/EC, 2009/72/EC).

[2] Evidence based on US data suggest that downstream liberalisation led to a decrease in patenting activity of upstream actors (Sanyal and Ghosh, 2013).

period of increased internationalisation of ownership at every stage of the electricity supply chain, which affected the location of R&D activities. Indeed, while OEMs were already operating across borders, supplying parts to non-domestic markets, ownership of firms operating in the downstream stages of the electricity supply chain which had, for the most part, retained a domestic focus, was transferred to foreign entities, potentially inducing the relocation of R&D activities (Jamasb and Pollitt, 2011).

With regard to changes in environmental policy stringency, jurisdictions around the world strengthened direct support for the development and deployment of renewable electricity generation technologies while at the same time increasing the (implicit or explicit) price on greenhouse gas emissions. In the US, while there was little policy initiative on the part of the federal government, several State legislatures introduced Renewable Portfolio Standards (see North Carolina Clean Energy Technology Center, 2019, for detailed State-level information). In the EU, and hence in the UK, the first such policy was the directive on the promotion of electricity produced from renewable energy sources in the internal electricity market (Directive 2001/77/EC). The transformation of the UK generation portfolio is now well under way, with the share of electricity produced from renewable sources having risen from 3.5% in 2000 to 24.6% in 2016 (Eurostat, 2018) and 35.8% in the first quarter of 2019 (BEIS, 2019), allowing it to reduce the CO_2-intensity of the said portfolio from 480g CO_2/kWh in 2000 to 246g CO_2/kWh in 2017 (IEA, 2018).[3]

This chapter sheds a descriptive light on the evolution of the characteristics of UK-based innovative actors in the ESI in the face of these structural changes, based on patent filings at the UK IPO over the period 1955-2016.[4] The focus on UK actors is motivated by both historical institutional developments and methodological constraints. Regarding the former, the UK has been at the forefront of key technological and policy developments, making it a particularly salient case-study for the purpose of our research. With respect to the latter, the scope of our study is limited by two factors. First, our patent selection approach involves the use of natural language processing techniques on patents' title and abstract and therefore requires to work in a single language (English in this case). Since patents have to be written in one of the official languages of the patent office at which they're filed, which may or may not include English, an extension of this approach to patents filed at other patent offices is non-trivial. In addition, the linking with business structure database, which we perform in section 4.4.3, introduces an additional hurdle to cross-jurisdiction analysis in the sense that the universe of firms that such databases cover varies across jurisdictions.

We make the following contributions. First, we provide a patent search methodology that uses a supervised learning classification algorithm (random forest) to identify patents pertaining to electricity supply technologies. The classification is based on n-grams derived from the

[3] Although the UK was slightly below the 2016 EU average (29.6%), this transition represents the 6^{th} largest increase among all EU member states over that period (Eurostat, 2018).

[4] At this stage, it should be noted that not all innovations are patented nor patentable (Jamasb and Pollitt, 2011) and hence patent filing counts should not be interpreted as providing an exhaustive account of innovation taking place with regard to specific technologies. However, to the extent that patent filings follow the trends in innovation activity, they provide an accurate proxy to capture them (Dechezleprêtre et al., 2011).

patents' title and abstract.[5] This approach allows us to address a standard shortcoming of keywords-based search, i.e. that the list of keywords is a subjective construction which might only partially account for the semantic field used by applicants to describe relevant inventions. In addition, it is flexible enough to allow identification of "lateral" innovation. Second, in contrast to a number of earlier studies – see section 4.2 – which focus on the impact of liberalisation and decarbonisation policies on aggregate innovation trends, we provide an in-depth discussion of the characteristics – and heterogeneity[6] – of (UK-based) actors carrying out innovation along the entire electricity supply chain, from OEMs to distribution companies. Third, compared to previous studies which tend to concentrate on generation technologies, it provides an industry-oriented perspective and broadens the technological focus so as to include all electricity supply technologies.

The approach taken in this chapter provided us with important insights. First, the innovation activity shifted away from large (integrated) generation, transmission and distribution utilities to (smaller) equipment manufacturers or R&D firms. Patent filings by universities, although increasing as a share of total patent filings over time, remain marginal. Second, the distribution of patent filings over the sample period is heavily skewed, with a small number of actors constituting a large proportion of filings. This is particularly true for OEMs. Third, on a related note, we uncovered the predominant role played by lateral innovation in the development of fossil fuel electricity generation technologies (FF). Fourth, innovation in these technologies still represents a large proportion of yearly filings. Finally, with regard to UK-based OEMs specifically, the chapter highlights a number of firm-level (technological) dynamics: (a) a majority of patents are filed by firms that are active in both fossil fuel and renewable electricity generation technologies (REN), (b) but 'mixed' firms have filed significantly more FF patents than REN patents; and only during the period 2007-2013 have these firms filed more REN than FF patents, (c) the increase in REN patent filings observed between 2005 and 2011 went hand in hand with an increase in the number of (small) technological entrants (i.e. firms patenting for the first time).

The rest of the chapter is organised as follows. Section 4.2 reviews the relevant literature and formulates hypotheses. Section 4.3 presents the construction of the dataset and section 4.4 analyses the dataset by (main) actors and technologies. Section 4.5 discusses policy implications. Section 4.6 concludes.

4.2 Innovation in the ESI – actors, technologies and incentives

Studying innovation activity at the sector level based on patent data presents a number of challenges. First, it calls for the identification of the intersection of *relevant* actors and technologies

[5] An n-gram is a sub-sequence of n-elements constructed from a given sequence. In the case at hand in this chapter, the sequence is a single string of (stems of) words (comprised of a patent's title and abstract) and the elements are the (stems of) words. Hence, for instance, a bi-gram is a string comprised of two (stems of) words.

[6] To our knowledge, only Noailly and Smeets, 2015 discuss the role of firm heterogeneity in the context of electricity supply technologies.

in order to construct the *relevant* set of patents – section 4.2.1. Second, given the diversity of innovative actors in the ESI, rationalising the observed patenting trends then requires a distinct discussion for each of them – section 4.2.2.

4.2.1 ESI actors and technologies

From an institutional perspective, innovative actors in the ESI – just like in any other sector – can be seen as belonging to one of the following categories: private corporations, government-owned non profit entities (e.g. vertically integrated utilities such as those existing prior to liberalisation), universities and research centres, individuals. This classification, introduced by the Centre for Research & Development Monitoring, 2017, is used in section 4.4.1.

From an industry perspective, the ESI is usually understood as comprising an upstream stage (OEMs) and downstream stage (generation, transmission and distribution operators). In its investigation of innovation activity in the sector, prior literature followed this dichotomy and studied innovation by upstream equipment manufacturers and downstream generation, transmission and distribution entities separately. This is in part a reflection of the difference in the nature of incentives to innovate faced by actors in each stage of the ESI. The overwhelming majority of earlier studies focus on generation technologies and, as a result, mostly discuss innovation by upstream equipment manufacturers. Relatively fewer studies have investigated innovation by downstream actors; notable exceptions are Jamasb and Pollitt, 2011; Jamasb and Pollitt, 2015 in the UK context.

One difference between upstream and downstream actors is that the latter are likely to have a narrower technological focus (i.e. on electricity supply technologies) whereas equipment manufacturers may have a more diversified innovation portfolio. Hence, unless these actors focus solely on electricity supply technologies, one cannot consider all patent filings by OEMs as pertaining to electricity supply technologies. Identifying filings specific to these technologies requires us to filter by specific keywords or (IPC/CPC) technological codes.

This is why prior literature examining the innovation activity in the ESI has mainly worked based on the identification of key technologies and associated technological codes.[7] Earlier studies relying on the identification of specific electricity supply technologies focused primarily – if not exclusively – on electricity generation technologies, a focus justified by the fact that early policy changes aimed at inducing innovation primarily in generation technologies. Johnstone, Haščič, and Popp, 2010 identifies IPC codes pertaining to renewable electricity generation technologies whereas Lanzi, 2010 develops a methodology whereby IPC codes for both general and efficiency-enhancing fossil fuel generation technologies are uncovered. Taken together, these studies provide a comprehensive list of IPC codes pertaining to electricity generation technologies, both renewable and fossil-fuel. The present study contributes to a more complete identification of electricity supply technologies by singling out IPC codes related to transmission and distribution technologies as well as other ESI-relevant technologies.

[7] Although the construction of patent datasets based on such an approach would in theory allow for a discussion around the actors by which they are filed, most studies do not include such a discussion.

4.2.2 Innovative actors and innovation incentives

Over the period under study in this chapter, innovation in electricity supply technologies was primarily carried out by three distinct groups of actors: public R&D institutions, integrated utilities and private firms. Each faced different constraints and incentives and played a different role in the development of electricity supply technologies, which we briefly review in this section.

4.2.2.1 Public R&D institutions and integrated utilities' energy research

The development of electricity supply technologies over the second half of the XXst century owes much to the innovation activities carried out by integrated utilities and public R&D institutions. Indeed, some electricity generation technologies (e.g. nuclear) were developed through dedicated institutions, which aroused from a commitment by public authorities to develop them. Such was the case, for instance, of the UK Atomic Energy Authority (UK AEA). The Authority, which initially oversaw the entire UK nuclear program, retained responsibility of solely research activities after a restructuring in 1971 (Atomic Energy Authority Act 1971). As highlighted by earlier literature (Jamasb and Pollitt, 2008; Jamasb and Pollitt, 2011) and as evidenced by our patent filing sample – see section 4.4.1 – the UK AEA played a prominent role in developing civil nuclear energy technologies as well as other related technologies. Furthermore, Jamasb, Nuttall, and Pollitt, 2008 noted that the decision break-up the energy laboratories previously operated by the UK AEA disregarded energy research policy considerations and was mostly a "side-effect" of competition policy. This had unfortunate consequences for the UK energy research activity, both public and private, since such large research bodies were also triggering innovation by private (smaller) entities.

4.2.2.2 Firms

Theoretical and empirical research into the drivers of innovation at the firm level suggest that (a) the competitive environment affects innovation incentives (Arrow, 1962a; Gilbert and Newbery, 1982), but the relationship is non-monotonic (Aghion et al., 2005);[8] (b) relative input prices and the policy environment can affect the direction and pace of innovation (Hicks, 1932; Acemoglu, 2002); (c) firms' innovation patterns (i.e. intensity and quality) are heterogenous and depend on structural industry or firm-level factors (Schumpeter, 1942; Mansfield, 1962; Kamien and Schwartz, 1975).

[8] Schumpeter, 1942 initially argued that (near-)monopoly firms in highly concentrated industries would have higher incentives and be better able to provide innovation than small competitive firms whereas Arrow, 1962a pointed out that, owing to several market failures, the private provision of knowledge would fall short of the (socially) efficient level, regardless of the market structure. A later investigation of the competition-innovation relationship suggested that this issue would be partly alleviated if the monopoly faced credible entry pressures (Gilbert and Newbery, 1982). Moreover, Aghion et al., 2005 highlighted that competition could have a different effect on innovation depending on the composition of the industry – if it is mostly populated by *neck-and-neck* firms, then increased competition will induce more innovation whereas if it is mostly comprised of *leaders-followers* then increased competition might reduce the incentives for followers to innovate and reduce overall innovation.

Several studies investigated these propositions in the context of the (UK) ESI. Regarding the liberalisation process, most of them investigated the impact of such reform on the actors directly affected, i.e. generation, transmission and distribution operators. In the UK, Jamasb and Pollitt, 2008; Jamasb and Pollitt, 2011; Jamasb and Pollitt, 2015 note a substantial decline in R&D in the electricity sector following liberalisation, which they attribute mainly to: (i) the positive correlation between public and private R&D spending in the UK electricity sector and the fall in public R&D over the liberalisation period; (ii) the fact that intensity of innovation activity is related to the (expected) payoff of innovation (Nemet, 2009) – by inducing competition among actors with low(er) market share, it reduced the market share of each individual electricity generator, thereby reducing the incentive to innovate.[9]

As Sanyal and Ghosh, 2013 showed, the introduction of competition in the downstream generation sector also affected the innovation activity of (upstream) equipment manufacturers. They show that following the Energy Policy Act, patent applications by OEMs at the US PTO declined substantially. Building on the theoretical framework provided by Aghion et al., 2005, they propose that this net decline is the result of "a negative pure competition effect outweighing the positive escape competition effect arising out of competition among the upstream EEMs, and the positive appropriation effect arising out of IPP entry downstream" (Jamasb and Pollitt, 2011, p. 314). The existence of a relationship between the structure of the downstream generation market and innovation by upstream equipment manufacturers is to be expected given that power suppliers (i.e. utilities) purchase innovation from upstream equipment manufacturers.

Next to the market structure, earlier literature also showed that market incentives and environmental policies affect the direction and pace of technical change. Popp, 2002 finds evidence that higher energy prices induce innovation in "clean" and energy-saving technologies whereas Porter and Linde, 1995 were the first to suggest that environmental regulation can stimulate the firms' green innovation activity, with Jaffe and Palmer, 1997 providing supporting empirical evidence to this claim.

The role of environmental and climate policies in shaping technological development was subsequently discussed in the more general framework provided by the literatures on endogenous growth and directed technical change, with the attention shifting towards the role of these policies in initiating and/or sustaining innovation in climate-friendly technologies (Jaffe, Newell, and Stavins, 2002; Newell, Jaffe, and Stavins, 2006; Popp, 2010). We learn from these literatures that innovation in the dirty or green product depends on the relative strength of the

[9] However, the development of new abatement technologies is linked to the existence of a demand for such technologies. The introduction of climate policies supporting such a demand might have counter-acted the negative effect of liberalisation. In that respect, Fischer (2008) develops a theoretical model showing that government support for emissions control R&D is only effective if there is at least moderate environmental policy in place to encourage adoption of the resulting technologies, suggesting that it is the combination of environmental and technology policies that leads most effectively to a technological transition.

market size and price effects.[10] It also suggests that whether – and to what extent – initiating such innovation processes requires government intervention depends on the assumptions made about the degree of substitutability between dirty and clean inputs.[11] Empirical evidence regarding these mechanisms was provided by Aghion et al., 2016 and Calel and Dechezlepretre, 2016, both using firm-level data. The former study highlights two interesting features: (i) that firms tend to innovate more in clean (and less in dirty) technologies when they face higher tax-inclusive fuel prices; (ii) that there is path dependence in the type of innovation (clean/dirty) both from aggregate spillovers and from the firm's own innovation history.

Finally, other advances in this strand of literature shed light on the heterogeneity of innovators and as a result provided more precise indications about the nature of innovation dynamics. Klette and Kortum, 2004 suggest that technological transitions can occur both through a shift of innovation activities within existing firms and through innovation entry and exit; Noailly and Smeets, 2015 point out that the empirical literature in this line of research documents several key stylised facts about innovating firms. Among them are the observations that: (i) the distribution of R&D intensity among firms is highly skewed, (ii) large established firms are very active innovators but tend to focus on improving existing technologies, (iii) more radical innovations are the preserve of small and new entrants.

4.2.3 Framework and hypotheses

The above literature provides valuable guidance for the analysis of innovation patterns by UK actors. First, innovation by private and public entities is correlated with levels of public R&D spending. Second, the set of actors performing innovation in the ESI and the relative weight of each type of actor is likely to have changed as a result of both liberalisation and environmental policy changes.

With the liberalisation of the ESI and the quasi-disappearance of public research institutions, most of the innovation activity – at all stages of the electricity supply chain – is carried out by private entities which, in turn, strengthens the need to understand the dynamics driving the innovation activity of such entities.

Therefore, after reviewing innovation by all actors identified in our sample we further characterise innovation by UK-based OEMs. By linking patent information with business structure data at the firm-level, we relate innovation activity to the firms' own knowledge stock, age and size. Furthermore, following Noailly and Smeets, 2015, we provide a discussion of firms' technological heterogeneity, making a distinction between technologically mixed and specialised

[10] The former encourages innovation in the larger market, the latter encourages innovation for the market with the highest price. Since the market for the dirty good is currently the relatively larger one, there is a risk that the market size effect drives the economy towards innovation in the dirty sector.

[11] If it is low, then permanent intervention is needed. Note that there are several views about this: on the one hand, the advocates of permanent intervention (e.g. William Nordhaus, Nicholas Stern) and, on the other hand, the supporters of a middle way, e.g. Acemoglu et al., 2012. Importantly, all views provide a rationale for intervention - the difference lies in the magnitude and temporality. Note, however, that Mattauch, Creutzig, and Edenhofer, 2015 find that, under certain conditions, a permanent carbon tax is the optimal policy even in the case of high elasticity of substitution between brown and green technologies.

firms, i.e. firms specialising in a single (generation) technology or in multiple (generation) technologies. We expect mixed firms to be larger and older and the bulk of climate change mitigation technologies innovation to be provided by smaller, younger new entrants (since higher energy prices and environmental policy, which became more stringent more recently, should trigger 'technological entry').

4.3 Patent data selection: Identifying ESI-specific patenting activity

The discussion in the present chapter is based on a sample of *priority* patent applications filed at the UK Intellectual Property Office over the period 1955-2016.[12] This choice is motivated by the focus of our study, which is (primarily) to identify UK-based innovation. Information related to these filings is extracted from the European Patent Office, 2018 Worldwide Statistical Patent Database (version Spring 2018) via PATSTAT online.[13]

4.3.1 Patent search methodologies

Using patent filings for our purposes presents two challenges. The first pertains to the standard limitations of patent data (Calel and Dechezlepretre, 2016), which only capture part of the innovation activity (Jamasb and Pollitt, 2011), and hence require that the observed trends be discussed with due regard to the nature of the technologies at hand as well as the broader patenting context.[14] That is, we need to: (i) understand whether the trend observed at the industry level simply follows an aggregate trend in patenting or if there is indeed some industry-specific pattern; (ii) make sure that these filings continue to capture some of the firms' innovation activity, given that filing at the UK IPO is not the only route available to seek protection in the UK.[15] To see the former, Figure 4.1 shows both the absolute and relative (i.e. as a share of total UK IPO patent applications) count of patent filings. Over the studied period, both the absolute and relative count follow the same pattern, suggesting that the absolute count of patent filings at the UK IPO does indeed reflect some industry-specific pattern. As for the latter, there continues to be a "home-bias" which induces inventors to file the first (priority) patent to the intellectual property office that is closest to "home" (Dechezleprêtre et al., 2011). In addition, given that filing at a national office is cheaper than filing at a regional office, the former allows

[12] This follows Jamasb and Pollitt, 2011, except for the fact that their sample also includes patents whose priority country is the UK filed at the EPO and WIPO. However, these latter filings are bound to be 'duplicates' and hence provide little additional information with regard to our objective of identifying UK-based innovative actors.

[13] The SQL queries used to query the PATSTAT database are provided in appendix C.2.1.

[14] The first comprehensive account of the economic relevance and availability for research of patent data was given by Griliches, 1990 but their use, which has grown dramatically over time as both the quality of patent statistics and their availability have increased, dates back to Bound et al., 1984. Furthermore, output measures of the innovation process are generally preferable to input measures such as R&D spending (Dechezleprêtre et al., 2011).

[15] Patenting at the UK IPO reached an all time high in 1969 (63614 filings) and decreased steadily until today (22072 filings in 2017). This includes direct and PCT applications. Yet, since the opening of the European Patent Office (EPO) in 1978, protection in the UK can be obtained via this route too. Total filings at the EPO were initially marginal (3598 in 1978) and became increasingly popular, especially since the early 1990s (60754 in 1990; 166585 in 2017).

inventors to swiftly acquire a filing of which they can claim the priority when they file a patent at the latter.

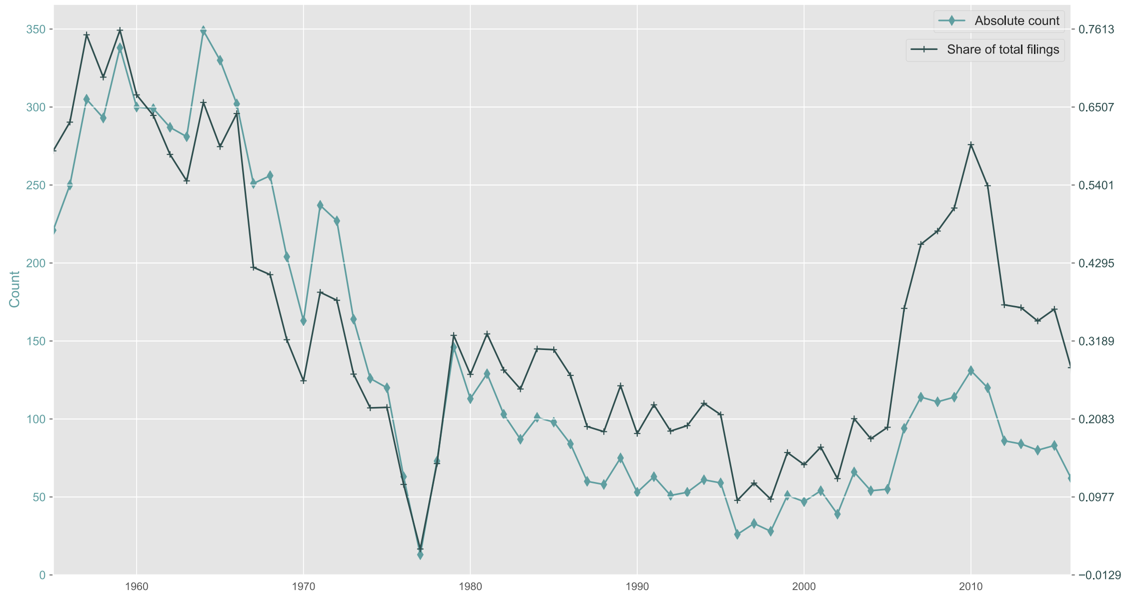


FIGURE 4.1: UK ESI patent applications, absolute count and share of total UK IPO filings

The second challenge arises because of a mismatch between the nature of our study – which investigates innovation trends at the sector level – and the structure of the patent classification system – which is based on technical features rather than sector of origin or “destination"(Hall, Jaffe, and Trajtenberg, 2001; Jamasb and Pollitt, 2011). As a result, identifying the galaxy of patents “relevant" to a particular sector of the economy must continue to rely on *ad hoc* search strategies. These usually take one of three forms – actor-based, keyword-based and technology-based – or combinations thereof (Jamasb and Pollitt, 2011). In the first approach, the patent search is based on the name of relevant actors (e.g. utilities, equipment manufacturers, research institutes,. . .). This, however, must either rely on the researcher’s prior knowledge of the actors’ names or on international classifications nomenclature (such as ISIC – or its European equivalent, NACE) to identify the firms belonging to specific sectors – see, e.g., Bound et al., 1984. The former might leave out patents submitted by smaller (and less likely to be known) actors while the latter might leave out actors whose primary affiliation is not the sector under scrutiny. Furthermore, while the number of downstream actors is relatively limited and the UK Office for Gas and Electricity Markets (Ofgem) maintains a list of licensed generation, transmission and distribution companies, the number of equipment manufacturers is potentially much larger, which makes a search based on their names impractical.[16]

The second approach relies on a list of keywords (and combinations thereof) and can be used for sector and technology oriented patent search. This addresses some of the limitations

[16] In the US, the Energy Information Administration maintains a list of equipment manufacturers – see Sanyal and Ghosh, 2013 – but no such list exist for the UK and, even if it did, it might not be exhaustive.

of the actor-based search but introduces new ones (e.g. subjectivity in the choice of keywords, inability to cope with strategic 'naming' behaviour on the part of applicants).

Finally, a third approach consists in identifying the patents using their International Patent Classification (IPC) or Cooperative Patent Classification (CPC) technology codes. This approach has been adopted in Dechezleprêtre et al., 2011; Dechezleprêtre and Glachant, 2014; Lanzi, 2010 and has been the approach taken to establish the EPO-CPC climate change mitigation technologies classes.[17] It relies on identifying the codes associated with the technology(ies) under scrutiny (i.e. electricity supply), which in itself is not immune to errors and the accuracy of which is likely to be higher for well-established technologies than for nascent ones.

4.3.2 Our patent search strategy

We develop a patent selection strategy that addresses some of the limitations highlighted above, minimises the measurement error, i.e. inclusion of irrelevant patents and exclusion of relevant ones (Dechezleprêtre et al., 2011), and is suited to our objectives of (i) identifying UK-based innovative actors along the electricity supply chain, (ii) identifying their innovation activity, (iii) supplement IPC classes list with codes relevant to transmission and distribution, and other relevant technologies. Our strategy, which combines supervised machine learning (ML) classification and actors-based patent searches, is described below.

We start with an initial dataset containing 346797 patent applications covering the innovation activity in the UK between 1955 and 2017.[18] This *core* patent dataset contains all patents with associated technology field(s) belonging to IPC categories 'B','F','G','H', with application authority GB and priority country GB over that period. Within that set, our patent selection starts with a keywords-based search on the patent title using keywords queries presented in Jamasb and Pollitt, 2011 and aimed at covering electricity generation, transmission and distribution technologies. This search identifies 3072 distinct patent applications.

However, one drawback of such an approach is that it depends on a subjective keywords list, which may not be representative of the semantic field describing all the relevant technologies; it therefore may only partially capture the set of relevant patents. To address this concern, we resort to identifying relevant patents using a random forest classifier on a subset of our *core* patent dataset. This subset is the set of patents with IPC classification codes associated with the patents identified by our initial keywords-based search. In doing so, we hope to include patents that may be relevant to the ESI but that have been missed due to the use of words not included in our list to describe the patented invention. The rationale behind this approach being that the relevant patents that may not use the same keywords should still have been assigned the same IPC class. The patent applications identified by the keywords-based search are associated with

[17] See https://www.epo.org/news-issues/issues/classification/classification.html for more information about this classification.

[18] This is the total number of patents with an abstract AND a title. Our initial patent search, which was truncated to return only patent applications with an abstract, returned 354760 patents, 7963 of which did not have a title and were excluded from the sample. In addition, note that we downloaded filings up to 2017 but later truncated our sample to 2016 to account for a lag between filing and actual recording in the database.

1936 distinct IPC codes, out of 50711 distinct IPC codes contained in our core dataset. This step produces a sample of 59757 patent applications, which is bound to include some patents that do not pertain to electricity supply technologies. Therefore, the last step of our ML approach is to distinguish between the patents relevant to electricity supply technologies and those that are not using a random forest classifier. The construction and training of the classifier is described in appendix C.1. It identified 3498 patent applications, 1811 of which had also been identified by the initial keywords-search.

This first search is complemented with an actors-based search, which targets only downstream ESI actors and relies on Ofgem's list of licensed electricity generators, transmission companies and distributors.[19] This list is complemented with entities identified in Jamasb and Pollitt, 2011.[20] The search proceeds as follows. First, we search the PatStat Standardized Names in our original set for matches with entities in our list. Second, we perform a manual check and remove incorrectly identified patentees.[21] This leaves us with 24 actors and identifies 3731 distinct patent filings. The list of actors for which at least one filing was found is presented in appendix C.1.

Table 4.1 summarises the results of our patent search strategy, broken down by main category of applicants, and offers a comparison between the two search approaches. As it turns out, most of the patent filings identified by the ML-based search are by original equipment manufacturers (77%), followed by filings by individuals (15%), the Electricity Council (EC) and the UK Atomic Energy Authority (2%) – UK AEA, universities (0.5%) and integrated utilities. The actor-based search, on the other hand, focused on downstream ESI actors together with some actors known to have played a significant role in the technological development of the UK ESI (e.g. the Electricity Council and the Atomic Energy Authority).[22] The overwhelming majority of patents identified by this search was filed by the UK AEA (85%), the remainder of the filings being distributed between generation companies (6%), integrated utilities (5%), and transmission and distribution companies (0.5%). Taken together, the ML search and the actors-based search provide us with a dataset containing 8389 patents, of which the largest proportion was filed by OEMs (44%), followed by the EC and the UK AEA (38%), individuals (8%), generation companies (3%), integrated utilities (2.5%). The table also highlights the complementarity of the ML and actors-based searches as there is few patents that are identified by both of them. This suggests that the patents filed by the actors identified in this chapter

[19]This list is publicly available through the Electronic Public Register, accessible at https://epr.ofgem.gov.uk/Document and contains all documents related to licenses granted under the Gas Act 1986 and the Electricity Act 1989.

[20]Note that we also performed a search based on the names of the Global Ultimate Owners of the entities present in Ofgem's list but that few – if any – of these patents were associated with electricity supply technologies. Global Ultimate Owners were therefore excluded from our "actors"' list.

[21]For instance, patent applications filed by 'BP CHEMICALS' are removed from the dataset as they are not related to electricity supply technologies.

[22]The UK AEA was created in 1954 and was at the time responsible for the UK's civil and military nuclear programme, contributing very significantly to innovation in nuclear electricity generation technologies. Following the Atomic Energy Authority Act 1971, only research activities remained with the Authority. The Electricity Council, on the other hand, was set up in 1957 and tasked to oversee the electricity supply industry in England and Wales. It maintained research activities throughout its lifetime, especially in fossil-fuel based generation technologies.

may make use of a (slightly) different semantic field than that used in the keywords-based queries and that constructed by our random-forest classifier.[23] In addition, we note that there is a significant difference in the filing activity of companies (especially OEMs and generation operators) and individuals. The former do, on average, file 5.9 patents over the period covered whereas the latter filed only 1.2 patents on average; suggesting that companies have more systematic and organised innovation activities leading to sustained patent filings.

TABLE 4.1: Patent searches summary (1955-2016)

	Actor type	ESI stage	KW	ML	Actors	ML ∩ Actors	Total
N. Patents	Companies	OEM	2364	3677	-	0	3677
		Generation	2	3	279	3	279
		Transmission	-	0	3	0	3
		Distribution	-	0	13	0	13
	Integrated utilities		10	11	222	11	222
	Universities		19	26	-	-	26
	Individuals		496	696	-	-	696
	EC & UK AEA		20	87	3189	87	3189
	Other		160	258	24	0	282
	All actors		3072	4759	3731	101	8389
N. applicants/ assignees	Companies	OEM	456	658	-	-	658
		Generation	2	2	10	2	13
		Transmission	0	0	2	0	2
		Distribution	0	0	4	1	4
	Integrated utilities		1	1	3	0	4
	Universities		14	18	-	-	18
	Individuals		428	571	-	-	571
	EC & UK AEA		1	1	2	1	2
	Other		88	128	3	0	131
	All actors		990	1379	24	3	1400

The number of applicants in the table above is based on an author-created unique entity identifier. It differs from the number of distinct 'psn_id"s associated with the identified patents since, at times, several of them refer to a single legal entity. Some patents that have been manually removed (e.g. motor vehicle internal combustion engine)

Finally, the sample of identified entities spans a wide range of NACE classes.[24] 34% of the patents identified by our search strategy are associated with companies whose primary affiliation is the NACE "28.1 Manufacture of general-purpose machinery" or "28.11 Manufacture of engines and turbines, except aircraft, vehicle and cycle engines" class (and not the "32 Electricity, Gas, and Steam" class), followed by class "25.3 Manufacture of steam generators, except central heating hot water boilers" – , and class "26.5 Manufacture of instruments and appliances for measuring, testing, and navigation". This is a reflection of innovation activity taking place at the level of equipment manufacturers and illustrates the challenges that relying on NACE classes might pose for the definition of an industry.

[23] Arguably, it would be possible to design the ML search and train the classifier on a different sample so as to increase the overlap. This would make sense if the researcher was interested in relying on a single type of search; it was not the avenue pursued in this chapter.

[24] Graphical evidence is presented in figure C.1.2 in appendix C.1.

4.4 Whose – and what – innovation?

Equipped with the patent sample presented above we review the patent filing activity in the UK ESI over the period 1955-2016.[25] After a brief review of the general trend in patent application filings over this period, we first shed light on the actors – or actor categories – from which they originate; with the view of identifying the evolution of patent filings across all industry actors – section 4.4.1. Next, we analyse the (technological) nature of these filings, shedding light on the technological transition that occurred – section 4.4.2. Finally, for a subset of actors, i.e. UK-based OEMs, we relate patent filings to firm-level business structure data – section 4.4.3.

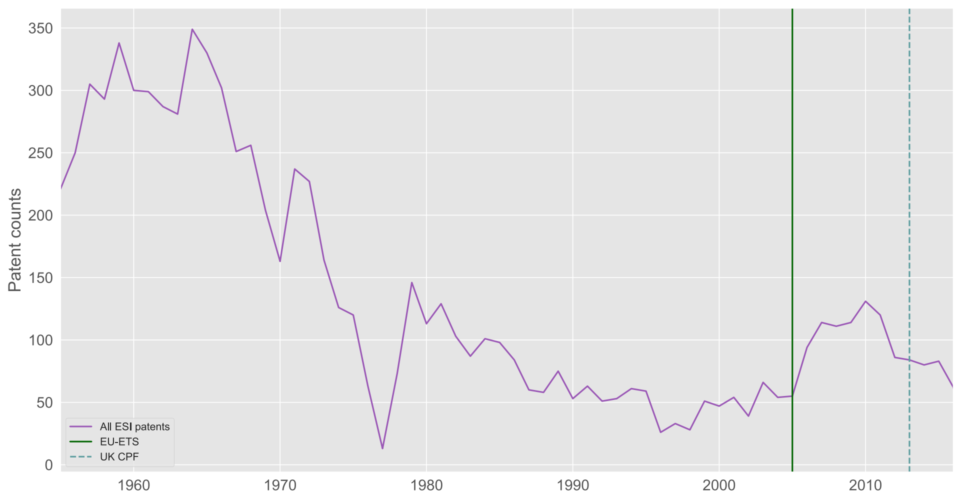


FIGURE 4.2: Patent applications at the UK Intellectual Property Office, 1955-2016

Aggregate trends are apparent in Figure 4.2, where we observe a clear decrease in total patent filing activity until the late 1990s, at which point an increase in filings relating to climate change mitigation technologies (as classified by the European Patent Office, 2013), brought about a revival in patenting. Put differently, yearly filings at the UK IPO averaged 244 patents/year between 1955 and 1976, and just 74 patents/year in the subsequent period.

4.4.1 Origin of patent filings

The aggregate trends observed above can be broken down according to the actors from which the filings originate. First, we distinguish between the main categories of patent applicants, as identified in section 4.2.1. Figure 4.3 presents the yearly patent filings introduced by each type of applicant, as a share of total applications in our sample. It clearly highlights the importance of three categories of actors: 'Company', 'Government non-profit' and 'Individual'.

[25]Given the existence of a lag between the reporting of patent filings by national patent offices and their inclusion in the PATSTAT database, we exclude the most recent year in the sample, 2017.

These categories account for 47%, 41%, and 8% of filings in our sample, respectively. In addition, the implications of the liberalisation and dismantling of vertically integrated utilities is indicated clearly by the change in the relative importance of patents filed by 'companies' and those identified as 'government non-profit' organisations at the start of the 1990s.[26] It also makes apparent the rise in importance of patent filings by 'individual' applicants which have mostly filed patents pertaining to REN technologies.

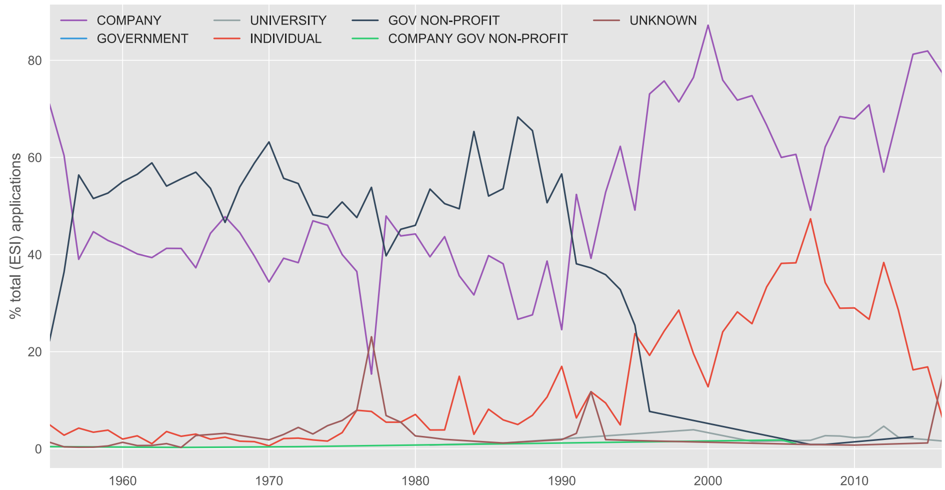


FIGURE 4.3: UK ESI patent applications, by type of applicant

Our second categorisation distinguishes between actors along the electricity supply chain. As alluded to earlier, we identify upstream OEMs and downstream generation, transmission, and distribution companies as well as vertically integrated entities (e.g. Central Electricity Generating Board) and two key actors of the UK ESI, the Electricity Council and the Atomic Energy Authority – see Figure 4.4. A striking feature of the picture painted by this figure is the predominant role played by OEMs. They were responsible for a significant share of total yearly filings (on average, 105.6/year between 1955 and 1977, 20.7/year between 1978 and 2000 and 52.9 between 2001 and 2016), the rest of it originating primarily from the UK Atomic Energy Authority and the Electricity Council.

From 1978 onward, patent filings by OEMs decrease slightly faster than those of downstream actors, altering the relative importance of each type of actors' contribution to total patent filings. Patent applications by generation, transmission and distribution actors at the UK IPO remained strong until the late 1990s – which corresponds to the full roll out of the provisions of the UK Electricity Act, while innovation activity by equipment manufacturers started dwindling as soon as the early 1970s. Interestingly, the patenting activity of OEMs remained stable throughout the liberalisation period and started increasing again towards the late 1990s. By

[26]This relative change in the origin of patent is somewhat "mechanical" and likely reflects the transfer of assets previously owned by vertically integrated utilities to private corporations.

the mid-1990s, OEMs represented again about half of total patent filings and, as patent filings by downstream actors almost vanished from 2002 onward, it represented an ever larger share of filings, accounting for most of the recovery in patent filings. Overall, insights provided by Figure 4.4 suggest that (i) original equipment manufacturers have always played a significant role in patenting activity, (ii) the relative importance of this activity has grown in recent years as patent filings by downstream actors dwindled to extremely low levels.

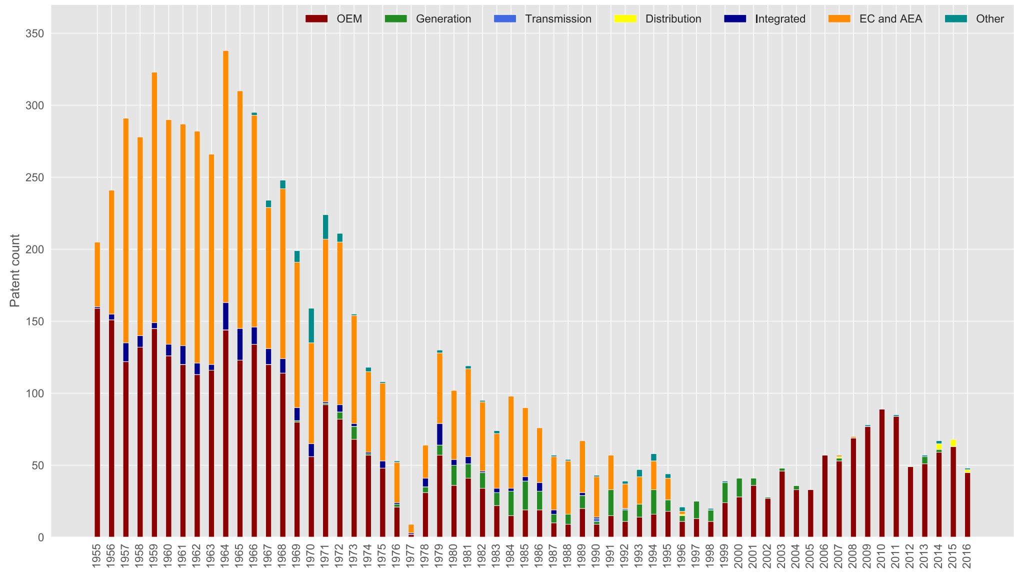


FIGURE 4.4: Annual patent filings in the UK ESI, by type of actor

This aggregate picture, however, hides a more subtle feature: the distribution of patent filings (among actors) is heavily skewed. This observation matches a well known trait of patent applications: they are concentrated within the hands of a few key actors, both at the country – most patents are filed in a small number of offices[27] – and sector level – within each sector, a few key players concentrate most R&D activity and patent filings. This is apparent in Figures 4.5 and 4.6, which present patent applicants over the period 1955-1990 (prior to liberalisation) and 1991-2017 (post-liberalisation), ranked in decreasing order of number of patent applications filed. We make a number of observations. First, quite unsurprisingly, the UK AEA tops the ranking over the period 1955-1990. Second, more interesting is the fact that Rolls-Royce has filed the second largest number of patents over the period 1955-1990 and the first largest over the period 1990-2016.[28] Over the entire period covered in our sample, it accounted for 41%

[27]The so-called IP5 group, comprised of the US Patent and Trademark Office (USPTO), the European Patent Office (EPO), the Japan Patent Office (JPO), the Korean Intellectual Property Office (KIPO), and the National Intellectual Property Administration (CNIPA formerly SIPO) in China.

[28]All of Rolls Royce's activities were part of a single entity until 1971, at which point its motor car activities were split from its aerospace, power systems and defence activities. The latter became part of a new entity, Rolls Royce plc. Figures 4.5 and 4.6 show the filings of the latter.

of patents filed by OEMs and 18% of all filings identified over the period. This observation is particularly interesting given that a number of Rolls-Royce's patent filings pertain to jet engine turbines rather than turbines specifically destined to be used in electricity generating power plants – see next section for further discussion. These filings nonetheless do bear relevance to electricity generation technologies to the extent that, as noted by Joskow, 1998, pivotal "innovations in CCGT technologies [drew] on complementary research on the development of jet engines for commercial aircrafts". This also explains the presence of entities like Power Jets (R&D) and Bristol Siddeley Engines among entities with the largest number of patent filing in this sample.

Turning to the post-liberalisation period, we observe the effect of both the dismantling of integrated utilities and the emergence of their privatised successors as innovative actors – with patents filed by National Power, Drax Power – and, among OEMs, the emergence of actors focusing on renewable technologies, especially wind – with about a hundred patents filed by the Danish company Vestas.

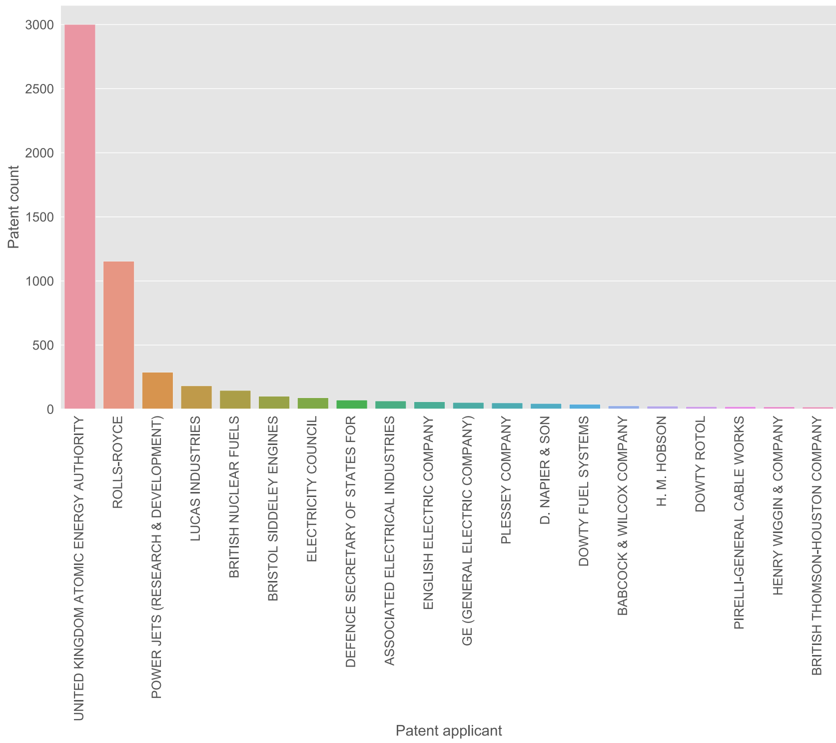


FIGURE 4.5: Patent filings, by assignee – 1955-1990

Finally, given the existence of a "home-bias", i.e. "the propensity for the priority country to be the same as the applicant's or inventor's country" (Dechezleprêtre et al., 2011), one would expect most patent filings in a dataset constructed based on priority filings at the UK IPO to have been made by UK-based applicants. While this is indeed the case, we note that some of the patent filings in our sample originated from non-UK actors, as observed in Figure 4.7.

This is mostly the case among OEMs, which have historically operated across national markets and sought protection for their innovation in their non-domestic/ export markets; whereas

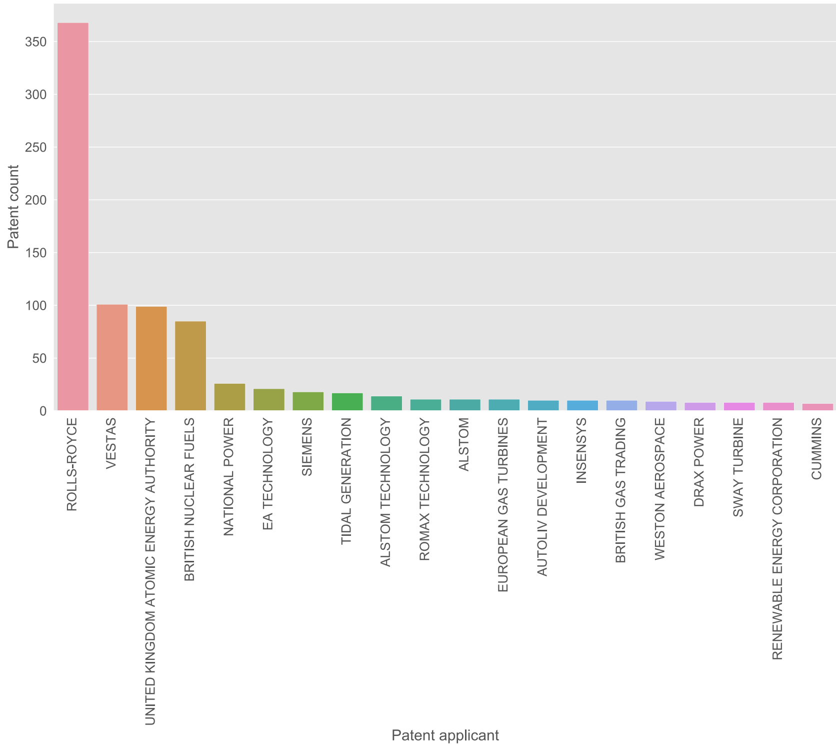


FIGURE 4.6: Patent filings, by assignee – 1991-2016

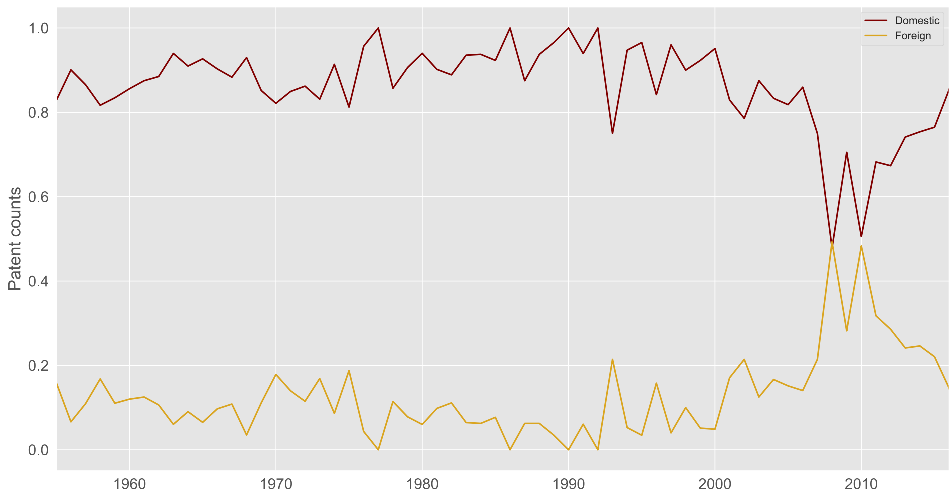


FIGURE 4.7: Share of patent filings by UK and foreign OEMs

downstream actors remained focus on their domestic markets, especially until the liberalisation of the sector. For this category of actors, in all years between 1955 and 2000 (excepted 1993), the proportion of priority patents filed at the UK IPO by UK applicants was above 80%. This proportion declined steadily between 2000 and 2010, and recovered thereafter. This suggests that the increase in filings by OEMs observed between 2008 and 2011 was partly due to the activity of entities based outside the UK.

4.4.2 Nature of patent filings

The discussion in the previous section sheds light on the (main) actors which have filed patents over the period under study. We now look at the type of (electricity supply) technologies to which they pertain. We make two main distinctions. First, between generation, transmission and distribution technologies. Second, within generation technologies, between renewables (REN), fossil-fuel (FF) and efficiency-enhancing fossil-fuel technologies (FF-E), and nuclear (NUC).

In order to allocate patents to specific technological categories, we rely on (IPC and CPC) technological codes. Depending on the technology at hand, these codes are identified either based on earlier literature or on our own research. Earlier literature provides the IPC or CPC codes related to REN (Johnstone, Haščič, and Popp, 2010; European Patent Office, 2013), FF & FF-E (Lanzi, 2010), and NUC generation technologies (European Patent Office, 2013). On the contrary, technology codes pertaining to transmission and distribution technologies or other ESI-related technologies have been less documented. To identify these codes, we proceed as follows. First, we read and review some of the patents in our sample and assign them to specific technological categories (generation, transmission & distribution, energy storage, other) and sub-categories (e.g. type of generation technology, core technology vs. manufacturing processes). Second, we identify, for each technological group, all associated IPC/CPC 4-digit classes, ranked in descending order of attribution (i.e. the class with the highest number of occurrences is listed first). Finally, we check the first classes to determine whether or not they relate to the technology at hand. This leaves us with a set of technology codes pertaining to our technologies of interest. Table C.3.3 in appendix C.3 provides a complete list of IPC/CPC codes used to classify technologies in this chapter.

This investigation confirms that not all patents in our sample are, strictly speaking, related to electricity supply technologies as identified by previous literature. In particular, the sample contains patents related to jet propulsion engines (and mounting thereof), instruments of measurement (e.g. radioactivity detection, utility metering,...), manufacturing processes of engines and turbines, general engineering and pollution control equipment. This is the case for two reasons. First, the actor-based search identifies patents by their applicant's name and therefore disregard their technological aspect. Second, the ML search was designed in such way that some *closely related* technologies would be identified.

In our sample, 3731 (44.5%) of patents relate to generation technologies and 248 (3%) to transmission and distribution. Within generation technologies, 936 (25%) patent filings pertained to renewables, 1464 (39%) to fossil fuel generation technologies, 264 (7%) to efficiency enhancing fossil-fuel generation technologies, and 1067 (29%) to nuclear energy.

Figure 4.8 presents the evolution of such filings and confirms that the majority of filings was directed at generation technologies, with very few filings pertaining to transmission and distribution technologies, except in the periods 1955-1965 and 2005-2015. Somewhat surprisingly, filings for efficiency-enhancing fossil fuel technologies remained low throughout the period under study. One also notes that the decline in patent filings relating to nuclear power since the mid-1960s only partly explains the decrease in total filings, especially since patent filings for renewable technologies remained fairly stable over that period.

Note that the paucity of filings for innovations pertaining to transmission and distribution of technologies might not accurately reflect the innovation activity in those technologies as most of it has been incentivised through Ofgem's Electricity Network Innovation Competition, which includes a requirement that innovation outcomes be disseminated and made available to other parties (Ofgem, 2017).

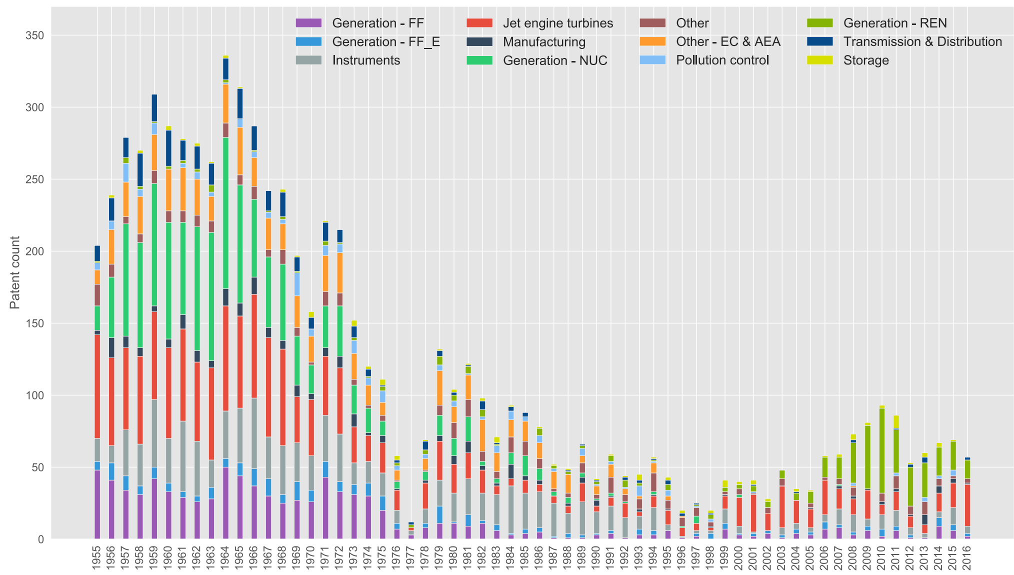


FIGURE 4.8: Annual patent filings in the UK ESI, by type of technology

In addition to the flow of filings presented above, we can also analyse the evolution of the industry *knowledge stock* over time, giving and indication of the knowledge base present in the UK ESI with regard to specific technologies. We focus on generation technologies. Figure 4.9 presents the discounted cumulative knowledge stock (proxied by the cumulative number of granted patents) of the UK ESI, using a 15% discount rate across all technologies (Hall and Mairesse, 1995).[29] We note that there is a steep increase in the industry's patent stock between 1960 and the early 1970s, primarily due to the increase in the stock of patents related to (i)

[29]Given that our dataset starts in 1955 and that we don't hold any information about the stock of patent filings prior to that year, we truncate the time series and disregard the first five years of our sample, presenting the evolution of the stock from 1960 onward.

fossil-fuel (ii) nuclear generation technologies. The stock of REN patents initially only rose very slowly, with the pace of increase rising slightly only toward the late 1970s. Interestingly, the value of the REN stock does not overtake that of NUC before the early 2000s (1990s if we include patenting by individuals) and not at all that of FF.

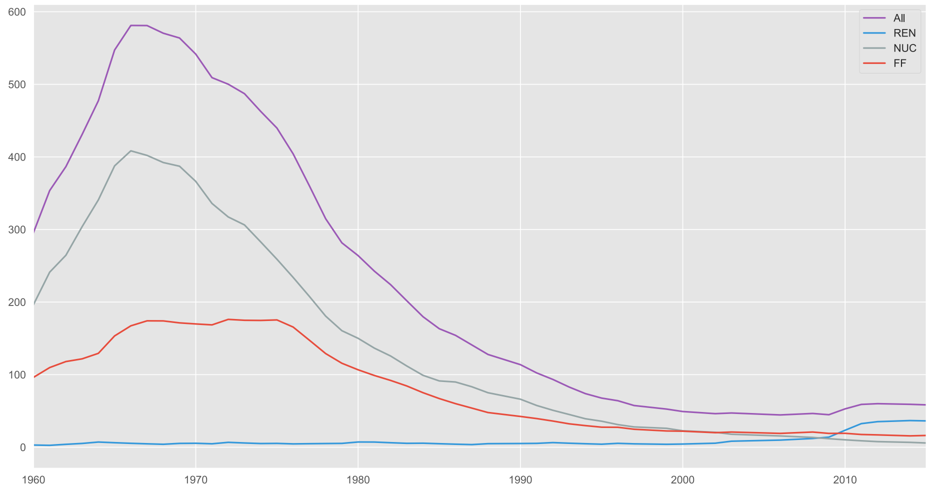


FIGURE 4.9: UK ESI discounted cumulative stock of granted patents, 1960-2016

4.4.3 Actors' characteristics and innovative output

Identifying trends in patenting activity provides valuable insights into the direction and pace of technological change but falls short of shedding light on their micro-foundations and, in particular, the heterogeneity of actors driving these developments. Building on the discussion in section 4.4.1, we analyse further these developments by matching patent filings with their corresponding legal entity using the patentee information associated with each application (provided in the PATSTAT database). The patent filing activity is then analysed in relation to filing history and firm business structure data such as age (using the date of incorporation) and size (number of employees and/or turnover). Information relating to the filing history is based on the patent sample identified above while business structure information is taken from the Bureau van Dijk, 2018 FAME database.[30]

4.4.3.1 Matching

Matching patent data with financial data requires that the patents be associated with the correct legal/financial entity. As highlighted by previous literature, this matching is rendered difficult by the fact that the recorded patent applicants differ from business entities. Indeed, a given

[30]Note that the patent applications data cover the period 1955-2016 whereas the business structure data only cover the period 1997-2016. In addition, our database contains the date of incorporation of each legal entity.

patenting entity may: (i) file applications under slightly different names (sometimes because of legal name change), (ii) apply under a name different to the corresponding legal entity, (iii) be a subsidiary (or plant) of a mother firm.

Regarding these issues, the OECD led an effort to (i) harmonise patent assignee names (Magerman, Van Looy, and Song, 2006) and (ii) link patent assignees with business entities. The former resulted in the creation of harmonised names for patent assignees (HAN) – PatStat Standardised Name (PSN) and associated ID – while the latter led to the creation a commercially available database – ORBIS-IP, Bureau van Dijk– containing both accounting and patent data. The harmonisation of patent assignee names did not, however, remove all duplicate entries (in some cases, multiple PSN's continue to refer to a single legal entity). Moreover, the standardised names do not necessarily correspond to the latest legally recorded name of the corresponding legal entity. Hence, in the absence of a common identifier linking patenting and legal entities (Bound et al., 1984; Torrisi et al., 2010), matching patent and business structure databases remains, despite recent advances, a non-trivial problem.

The researcher is thus faced with the following choice regarding their overall matching strategy: adopt and automated matching procedure based on secondary identifying features such as company names and postcodes present in both databases or manually assign an identifying number to the patentees that is also present in the business structure database (e.g. company registry number).[31] In both cases, the aim is to match all identified patentees with (at most) one legal entity identifier.

Given that we do not have (bulk) access to the FAME database data, we resort to a version of the latter option. First, using table tls207_pers_appln of the PatStat database, we associate the patent filings in our dataset with their patenting assignee, corresponding standardised names and id number as well as postal addresse(s). Next, we associate (each of) them with their corresponding Company Registration Number (CRN), retrieved from the UK Companies House's website. The assignment makes use of information on entity name and postcode obtained from the Centre for Research & Development Monitoring, 2017 Person Augmented Table. However, since the address information contained in the table did not record the latest address of some of the legal entities, it was necessary to update that information using Companies House's register information. This allowed to find correspondences between past and current business register addresses and, given that, a patentee's harmonised name and a company's registration number.[32]

[31] The former approach is possible when working with a database like FAME (or ORBIS), which contains current and past names of legal entities but is not appropriate for Business Structure Databases (business registers) of National Statistics Offices, which usually contain an anonymised identifier rather than an entity's name. See earlier literature, e.g. OST, 2014 execute a fuzzy matching between the EPO patent standardised names and Bureau van Dijk firm-level datasets (European Patent Office, 2018; Bureau van Dijk, 2018) on a key combining both of the above features.

[32] As alluded to earlier, some of the standardised name entries identified at this stage refer to the same legal entity and are therefore associated with the same CRN. We aggregate at the firm (i.e. legal entity)-level, retaining the CRN and the entity's most recent name and each entry is then associated with its patent portfolio and business structure variables. The matching results in a mapping file which records a legal entity's psn_id, psn_name, Company Registration Number. It also records the type of ESI actor (OEM, Generation, Transmission, Distribution) and whether it was identified by the keywords- or actors-based search.

Table 4.2 summarises the matching for applicants identified as 'companies', leaving out individual applicants and government non-profit organisations. From Table 4.1, we recall that there were 677 such applicants. Among those, 428 were identified as UK-based applicants, 180 as foreign applicants, and 69 remain unidentified. In terms of patent filings, this means that we were able to match 2925 (95%) of the patents filed by UK OEMs,[33] all of the patents filed by UK electricity generation (279) and transmission (3) companies, and 12 out of 13 of the patents filed by UK distribution companies. Finally, note that 604 (16%) patents filed by OEMs were so by foreign entities, and 148 patents were filed by applicants that could not be identified either as a UK or a foreign company.

TABLE 4.2: UK patents/applicants matching summary

	ESI Category	Matched patents	Matched applicants
Count	OEM	2925	411
	Generation	279	13
	Transmission	3	2
	Distribution	12	3
	All actors	3241	428
Share*	OEM	0.8	0.62
	Generation	1	1
	Transmission	1	1
	Distribution	0.92	0.75
	All actors	0.88	0.63

* Share of total number of 'COMPANY' applications or applicants.

4.4.3.2 Innovation by UK OEMs & business structure

In section 4.4.1, we established that the relative importance of OEMs in filing activity had grown over time, and especially so since 2002. We therefore seek a further understanding of the characteristics and innovation dynamics of these actors, focusing on those whose activities are located in the UK.[34] In particular, we investigate the patterns of technological entry and exit (Malerba and Orsenigo, 1999), the “technological inertia" (path dependence) that characterises patent filings at the firm-level, and their relationship with two key firm structure characteristics, age and size.

Following Noailly and Smeets, 2015, we distinguish between technologically mixed firms – which innovate in at least two types of electricity generation technologies – and specific firms – which innovate in only one of them. This latter classification is based on the composition of the cumulative patent portfolio of the firm in the last year of the sample (2016). Technologically heterogeneous firms are labelled 'mixed' whereas technologically specialised firms are labelled 'green', 'brown' or 'nuclear', depending on whether their cumulative patent portfolio contains only REN, FF or FF_E, NUC patents, respectively. Firms that do not file patents in generation

[33] This represents 80% of patents filed by all OEMs.

[34] We leave out downstream actors as their innovation activity has been the focus of prior studies, e.g. Jamasb and Pollitt, 2011; Jamasb and Pollitt, 2015.

technologies but do patent in other technologies are labelled as 'other'. Within our set of UK OEMs, 36% of the firms that have patented are 'green' firms, 12% are 'brown' firms, 4% are 'nuclear' firms, 4% are mixed firms. The remaining firms (46%) filed patents only in non-generation technologies.

Figure 4.10 shows the number of patent filings by each type of firm. Filings by technologically mixed firms have consistently outstripped filings by either their brown or green counterparts (except in 2007-2010 and 2012-2013). Given that these constitute only 3% of the firms in our sample, it suggests that, on average, they have a larger patent portfolio than technologically specialised ones. Moreover, Figure 4.11 suggests that this portfolio is skewed towards FF and FF-E electricity generation technologies: REN filings by mixed firms remained below the number of filings for FF and FF-E generation technologies in every single year in the sample and are extremely few. Interestingly, these filings exhibit an extremely strong correlation with patent filings pertaining to jet engine turbines, which further supports our claim that the technological development of FF technologies was 'complementary' to an existing knowledge base in the UK industry.

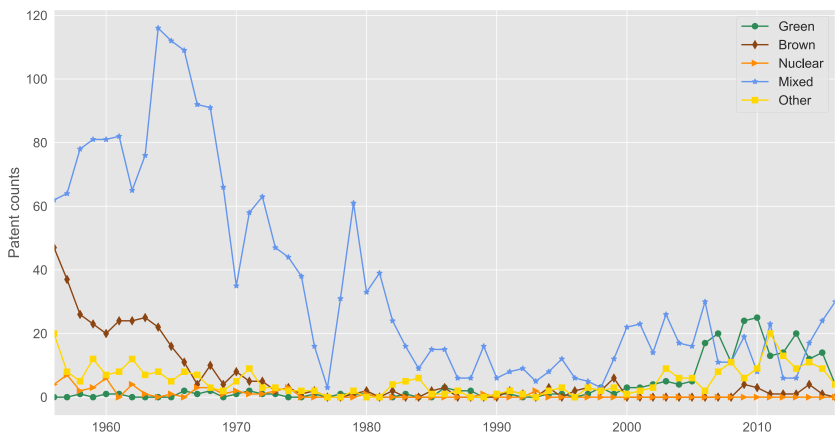


FIGURE 4.10: Patent applications by UK OEMs, by firm type

In light of the total number of REN patents filed by OEMs over the period, and especially in the years 2000-2010, the above observations suggest that the notable increase in patent filings for these technologies has been driven mostly by new (technological) entrants focusing specifically on them rather than by (older) mixed firms. This warrants a closer look at entry and exit dynamics.

The technological entry of a firm is defined as the first year in which it files a patent in the technological categories under consideration in our sample, regardless of its patenting history with respect to other technologies. Exit, on the other hand, is defined with respect to its discounted cumulative stock of patents: a firm is considered to exit the technological innovation

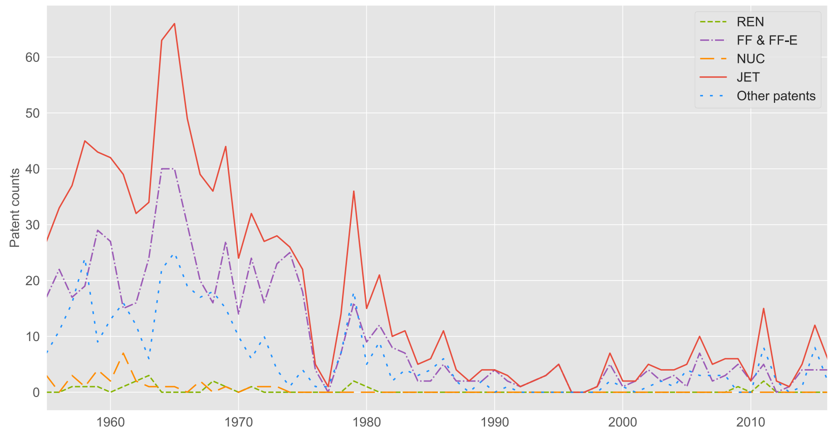


FIGURE 4.11: Patent applications by mixed UK OEMs

market if the said stock reaches 0. It is calculated in the same way as at the industry-level using to the perpetual inventory method with a discount rate of 15% (Hall and Mairesse, 1995). Figure 4.12 presents the evolution of technologically active OEMs over the period 1955-2016.

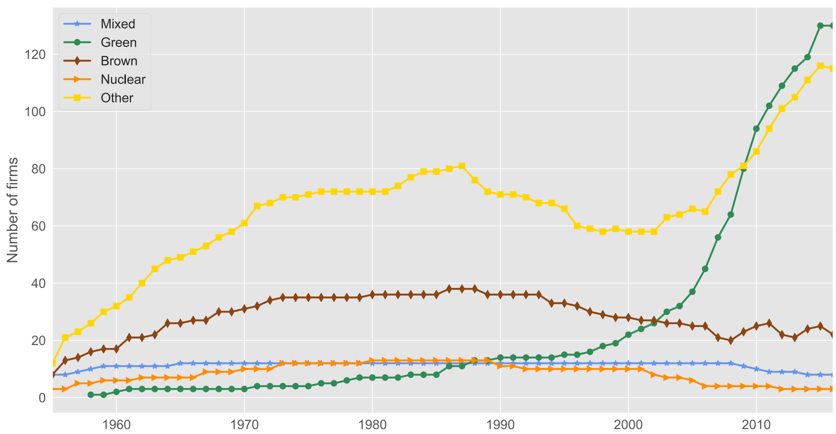


FIGURE 4.12: Technologically active firms, by firm type

The trends depicted indicate a rapidly increasing number of firms active in FF technologies until the early 1970s, corresponding to the development of fossil fuel fired power plants post WWII and public R&D funding for fossil fuel technologies – see figure 4.13. This increase is sustained – albeit more moderately – through the late 1980s, at which point the number of active brown firms starts decreasing steadily until it stabilises just above 20 in the late 2000s. The number of active mixed and nuclear firms follow a similar upward trend until 1980, at which point they both stabilise at 16 active firms. In the early 2000s, the number of active nuclear firms starts decreasing steadily. Finally, the number of active green firms grew steadily but slowly between 1958 and the mid-1990s, before experiencing an almost exponential increase from 1995 onward.

This is reflected in (technological) entry rates, which were significantly higher than the average during the years 2005-2011 for green firms than during the rest of the period. The average entry rate over the period 1960-2016 is 4.4% whereas it was 11.1% between 2005 and 2011. Given the large number of green OEMs filing patent applications since 2002 – above 5 in every single year – this implies that several of these applicants were new entrants, each filing on average a small number of patents. Table 4.3 provides further precision with regard to that observation. In every single year of our sample, green firms have indeed, on average, filed less patents than brown firms. In addition, there also seems to be a difference between firm type as mixed firms filed, on average, a higher number of both REN and FF patents than technologically specialised firms.

TABLE 4.3: Firm patenting activity: summary

Variable	Firm type	Mean	Median
REN patents	Green	0.023	0
	Brown	-	-
	Nuclear	-	-
	Mixed	0.025	0
	Other	-	-
FF patents	Green	-	-
	Brown	0.04	0
	Nuclear	-	-
	Mixed	0.67	0
	Other	-	-
Year of first REN innovation	Green	2005	2009
	Brown	-	-
	Nuclear	-	-
	Mixed	1972	1961
	Other		
Year of first FF innovation	Green	-	-
	Brown	1977	1968
	Nuclear	-	-
	Mixed	1963	1956
	Other	-	-
Year of first innovation	Green	2005	2009
	Brown	1974	1968
	Nuclear	1967	1972
	Mixed	1966	1961
	Other	1987	1994

Finally, we relate these observations to some of the firms' own characteristics. First, the literature on directed technical change reviewed above suggests the existence of a path dependency in innovative activity – see also (Crespi and Scellato, 2015). Using firm-specific (discounted) knowledge stocks based on their patents filing history since 1955 (calculated, as in section 4.4.2, with the perpetual inventory method and a 15% discount rate), we investigate the correlation between a firm's knowledge stock and it's patenting activity. This correlation is positive across all firm types, and is highest for technologically mixed firms (0.84), followed by that for brown (0.66) and green (0.57) firms. The lower correlation observed for green firms is somewhat unsurprising given that most of them are recent innovators and have not been found to be the source of sustained innovation thus far.

Second, we investigate the relationship between innovation and firm age and size in our sample. While age (based on the date of incorporation) and innovation history are available for all years in our sample, our proxies for firm size (employees/turnover) are only available for the period 1997-2016. Even if a discussion of causal links between these variables and the probability of patenting in one or the other technological category is beyond the scope of this study, we can nonetheless provide some empirical evidence. In particular, we look at the value of these variables at the time of technological entry, broken down by firm type.

The evidence provided in Table 4.4 suggest that green and mixed firms were on average 9 years old at the time of their first patent filing whereas brown firms were significantly older, 14 years old on average. However, on average, green firms were smaller than brown firms but larger than mixed firms at the time of their first patent filing.

TABLE 4.4: Firm characteristics at time of first patent filing, by firm type

Variable	Firm type	Count	Mean	Std. dev.	Median	Min.	Max.
Firm age	Green	106.0	9.72	13.62	4.0	0.0	92.0
	Brown	14.0	18.57	18.5	8.0	0.0	50.0
	Mixed	3.0	34.0	3.61	33.0	31.0	38.0
	Nuclear	1.0	40.0		40.0	40.0	40.0
	Other	78.0	15.923	20.82	8.0	0.0	117.0
Employees	Green	20.0	715.25	2214.48	64.5	3.0	9989.0
	Brown	7.0	13156.29	29535	1633.00	55.0	80000.0
	Mixed	3.0	37633.33	2136.2	38500.0	35200.0	39200.0
	Nuclear	1.0	2614		2614	2614.0	2614.0
	Other	37.0	2134.16	5548.41	534	3.0	32479.0
Turnover (GBP)	Green	24.0	60310.5	187918.85	6105.0	1.0	924700.0
	Brown	7.0	2597907.0	6292723.56	241300.0	6425.0	16864000.0
	Mixed	3.0	7380333.33	2628317.02	5939000.0	5788000.0	10414000.0
	Nuclear	1.0	785200.0		785200.0	785200.0	785200.0
	Other	37.0	965798.11	3323126.41	71663.0	70.0	19079000.0

4.4.3.3 Innovation by UK OEMs & external drivers

This section discusses the trends highlighted in sections 4.4.1 to 4.4.3 in light of some of policy and market factors that could affect them. First, we note that the pattern of patent filing, both in aggregate and at the technology-level, continues to exhibit co-movement with public energy R&D spending. This is in line with, e.g.,Johnstone, Haščič, and Popp, 2010; Dechezleprêtre and Glachant, 2014, which find a positive effect of publicly funded R&D on patenting, and with the evidence of spillovers between academic research and some types of government R&D and the private sector.

In addition, as noted by (Popp, 2017), governments around the world continue to use energy R&D budgets as a key policy tools, not least as part of their climate change mitigation strategies. This line of work reminds us that, however central R&D by private institutions is to knowledge accumulation, innovation by and the role of other energy “research institutions"

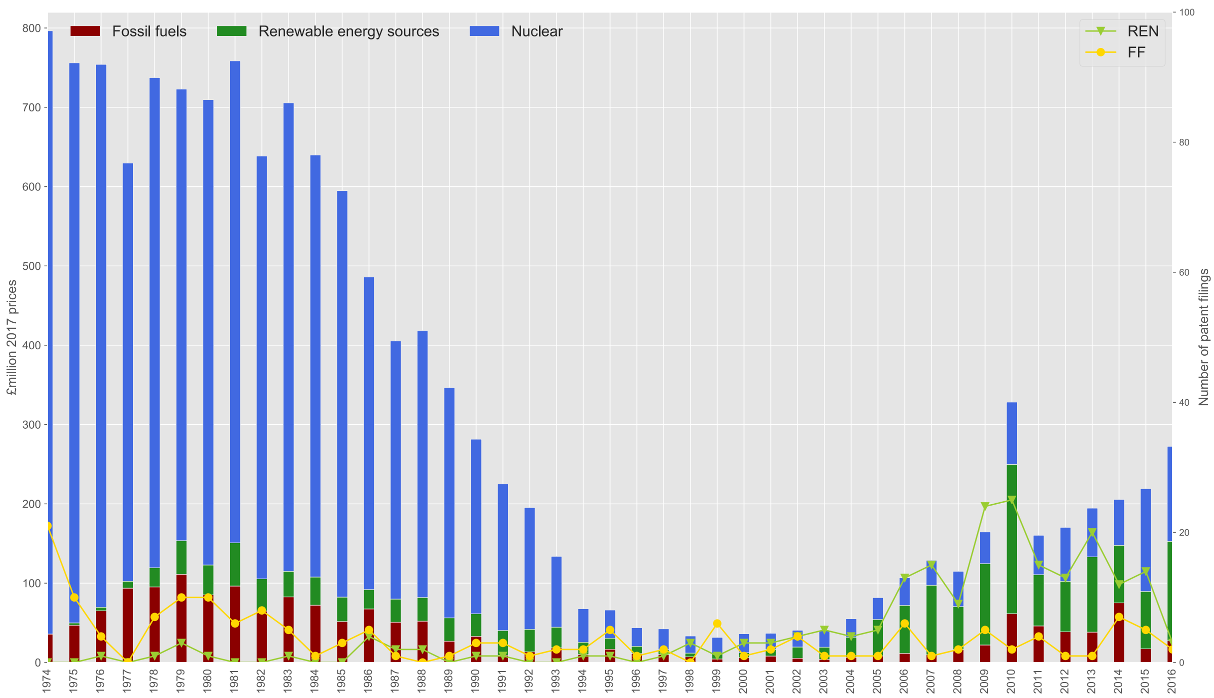


FIGURE 4.13: Public energy R&D spending and patent filings, by technology

(e.g. national laboratories,...) in sustaining the industry's aggregate innovating activity cannot be ignored. In fact, "research not only funded but also performed by the government does appear to play an important translational role linking basic and applied research." (Popp, 2017)

Second, our review of the literature also pointed at the importance of the market environment for firms' innovation activity. In particular, we highlighted the relevance of (i) market incentives (e.g. oil prices) (ii) public policies (e.g. climate policy). Figure 4.14 shows patent filings in REN technologies together with a fossil fuel price index for the UK and the nominal EU ETS allowance price (in EUR/tCO_2e) taken from chapter 2. The co-movement is apparent.

4.5 Discussion and policy implications

The analysis presented above discussed the trends in patent filings in the UK Electricity Supply Industry over the period 1955-2016. This analysis identified the set of UK-based actors from which these filings originate and, in particular, shed a more precise light on innovation activity by upstream original equipment manufacturers. The trends identified in the sample of patents used in this study confirms the decline of innovation by downstream UK ESI actors and the shift of this activity toward upstream OEMs. The shift out of the UK of innovation by downstream actors following liberalisation and their passage into foreign ownership was already documented (Jamasb and Pollitt, 2011) but this study presents a further confirmation of this observation.

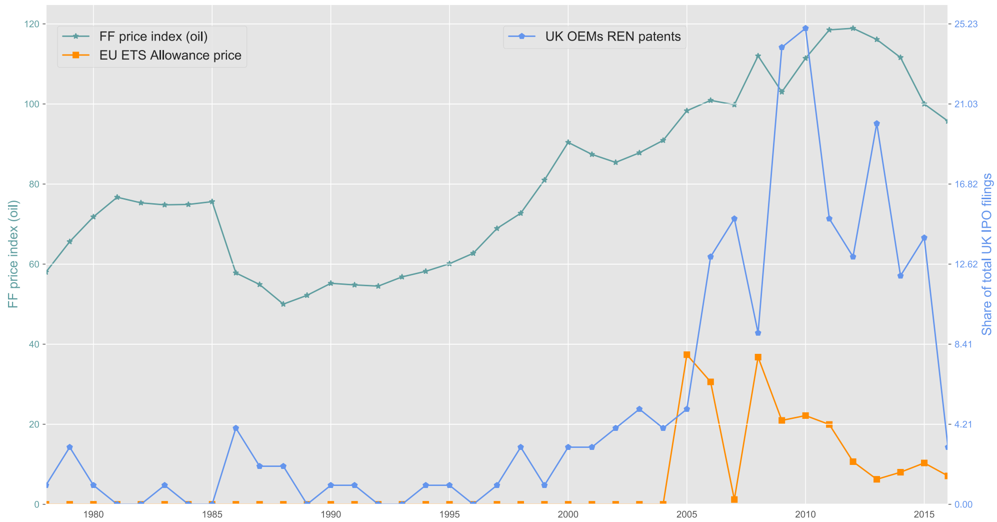


FIGURE 4.14: UK OEMs REN patent applications and fossil fuel & carbon prices (1978-2016)

Second, the first part of the analysis also highlights the role of a few large public (e.g. UK AEA) or private (Rolls-Royce Plc) actors in the development of specific technologies. The UK AEA was instrumental in the development of nuclear electricity generation technologies whereas Rolls-Royce, building on its expertise in the design of jet engine turbines, played a crucial role in the development of fossil-fuel based electricity generation technologies. This highlights that large institutions have the potential to trigger innovation activity among a large set of actors across the industry, strengthening the case for (public) support for these institutions. Further evidence of this observation could be obtained by looking at the co-patenting activity of these actors.

Next, we observed that a conjunction of increased UK energy R&D spending, strengthened climate policy and high fossil fuel prices might have induced an acceleration of innovation activity between 2006 and 2010, especially by generating a high number of small new (technological) entrants in REN technologies. Indeed, a notable observation of this analysis was that innovation in renewable generation technologies has been brought about by new, small and technologically specialised firms; which might have been helped by the lower sunk cost to R&D in such technologies compared to FF or NUC electricity generation technologies. The immediate policy implications of these observations is that in order to sustain innovation in these technologies, governments ought to (i) tailor policies in ways that specifically support (the growth of) young, small firms, (ii) keep barriers to entry low.

However, the revival in priority patent filings pertaining to these technologies does not seem to have been sustained, questioning whether the UK policy environment was appropriate to turn these firms into sources of sustained innovation.[35] Moreover, while a significant

[35]We note, however, that part of this decrease in filing activity might be related the maturity of technologies, which in itself might lead to a decrease in the propensity to patent and hence to lower patent filing activity (Haupt, Kloyer, and Lange, 2007; IEA, 2019).

proportion of recent innovation activity was directed at REN technologies, filing in FF technologies has continued, suggesting that little reallocation of R&D resources has taken place within firms. This should concern policy makers looking to make the power sector quickly transition to REN technologies. Hence, improving our understanding of how to incentivise within firm resource (re)allocation constitutes an important research theme.

Finally, we reemphasise the scope of the study and point to additonal avenues for further research. First, the analysis was based on a sample of priority patent filings at the UK Intellectual Property Office. While this is in line with the objective of the study, it is important to note that these filings might not represent all filings by UK-based actors. Indeed, these entities may have filed (priority) patents either at other national patent offices, at the European Patent Office or at the World Intellectual Property Office. In that respect, searching for all priority patent filings by the actors identified in this study (based on their PATSTAT psn_{id}) could shed further light of the results discussed here. Second, we note that the set of patenting actors was identified based on a sample of patents retrieved through an ML and actors-based search. This approach implies that we have identified actors that have filed at least one patent over the period 1955-2016 but that we do not observe actors relevant to the ESI but that have not filed any patent over the period. In other words, our sample provides information about the intensive margin rather than the extensive patenting margin. Third, the discussion presented in this chapter pertains specifically to the filing dynamics. As such, this study can't shed light on the value of the decline of institutions like the UK AEA or Electricity Council.

4.6 Conclusion

The world's commitment to keeping global average temperature increase below 2°C makes the further reduction of GHG emissions by the electricity supply industry in developed and developing economies alike an absolute necessity; even more so if the decarbonisation of other sector of the economy is to be achieved by their 'electrification'. This will require further deployment of existing CO_2-abating technologies and the development of new ones. However, the latest patent filing data available suggests that innovation by UK-based actors has slowed. Moreover, among these declining filings, those related to FF technologies have picked up again. These trends must be reversed.

Given the predominant role that OEMs seem to have recently acquired, understanding the innovation patterns of these entities is of the essence. In this respect, the above analysis highlighted a few salient observations: (a) a majority of patents are filed by firms that are active in both fossil fuel and renewable electricity generation technologies (REN), (b) but 'mixed' firms have filed significantly more FF patents than REN patents; and only during the period 2007-2013 have these firms filed more REN than FF patents (c) the increase in REN patent filings observed between 2005 and 2011 led to an increase in the number of technological entrants (i.e. firms patenting for the first time).

The evidence available so far shows that while prior policies have been successful at triggering technological entry, it has failed to create a (self-)sustained stream of innovation in “green" electricity supply technologies. Hence, the analysis suggests that any successful policy aiming at reversing the above trends ought to focus on supporting young, new entrants and turn them into sources of sustained innovation. This is especially important given that, at present, there is no large (UK-based) innovation actor in such technologies that could play a similar role as Rolls-Royce did for fossil fuel-based technologies.

Finally, we note that, historically, in the UK and other OECD economies, this innovation activity has originated from a variety of actors, ranging from government-owned vertically integrated utilities or research bodies to private entities, especially original equipment manufacturers and that innovation activity across this range of actors has been closely related to public authorities’ strategic technological choices and energy R&D funding.

Given that other electricity supply systems may, now or later, find themselves at a similar stage of their transition to a decarbonised electricity generation portfolio as the UK, its experience should be of particular interest to them.

Chapter 5

Conclusion

Anthropogenous climate change represents an unprecedented threat – both in scale and nature – to the well-being of Humanity. Unabated accumulation of greenhouse gases in the atmosphere will lead to changes in global and regional climate patterns that are likely to put extreme pressure on human populations and threaten the viability of many natural life-supporting systems (IPCC, 2014). In December 2015, the international community agreed to limit the increase in global average temperature to well below 2°C in an attempt to increase the chances of avoiding the most adverse effects of climate change. The results of this thesis suggest that the current mitigation regime, comprised of a mesh of international multilateral environmental agreements and national policies, is inconsistent with that objective.

This, together with insufficient technological advances in GHG-abating technologies, means that the world is still without an insurance policy to hedge against the possibility of catastrophic climate change. To achieve the objective of the Paris Agreement, and the UNFCCC more broadly, further policy and technology developments are needed.

This thesis was started out of an acknowledgement of this observation and the strong desire to understand how to (i) strengthen climate policy ambition and (ii) accelerate the technological transition to GHG-free technologies. With regard to the former, we explored the role of two sets of factors, the domestic political economy and the international environment, which the available evidence suggested had played a prominent role in shaping policy developments over the last 30 years. Regarding the latter, we investigated the role of firm-level innovation dynamics in electricity supply technologies, which are key to the achievement of economy-wide decarbonisation, in the United Kingdom.

As our discussion draws to a close, it is time to review the insights gained throughout.

5.1 Assessing climate policy ambition: carbon pricing

In pursuing our objectives, something became clear very quickly: that an improved understanding of the dynamics we were trying to uncover could only be built on the footing of a more robust assessment of the policies that are to be part of jurisdictions' climate change mitigation policy toolbox.

We undertook to build such an assessment for one type of climate policy: carbon pricing.[1] This resulted in the creation of an economy-wide emissions-weighted price and its calculation for 135 national jurisdictions and 63 North American sub-national jurisdictions. Given that a growing number of national and sub-national jurisdictions are adopting carbon pricing mechanisms, this standardised approach to their assessment constitutes a significant step forward in the understanding of climate policy developments.

This standardised metric allowed us to uncover a prime instance of the inconsistency between the world's stated global average temperature warming objective and currently implemented policies. Indeed, as of 2018, the world's average carbon price remains extremely low, at about 1.5USD/tCO_2e. This evidence provides a striking summary of the difficulty with which jurisdictions around the world have moved forward with the introduction of policies putting an explicit (and easily observable) price tag on GHG emissions.

The discussion in chapter 2 found that this weakness is rooted in two main sources. First, relatively high "flagship" nominal carbon prices in some jurisdictions are weakened by both sectoral price and coverage exemptions. Indeed, the move towards carbon pricing or the strengthening of existing schemes has been characterised by significant inertia and the passage of the required legislation has encountered substantial political economy hurdles, which could only be overcome using such exemptions.

Second, jurisdictions that do price carbon represent a small and/or shrinking share of world GHG emissions.[2] For instance, the GHG emissions of the European Union (EU), which represented 17% of world emissions in 1990, fell to 9% in 2016 (Gutschow, Jeffery, and Gieseke, 2019). Hence, even if the EU started pricing a significant share of its domestic CO_2 emissions in 2005, and in spite of a recent increase in the price of European Emission Allowances due to the latest reform of the EU-ETS, its domestic contribution to the resolution of the global stock externality might be limited.

Yet, one should not underestimate the value of early experiments. Not only did these policy developments lead, in some cases, to significant emissions reductions but they also constitute an invaluable source of institutional knowledge to build on when it comes to strengthening the national and international climate change mitigation policy regime. It is precisely in this knowledge and evidence that we tapped in order to build a further understanding of how to tackle the political and technological inertia that have hindered emissions reduction so far.

[1] While a standardised assessment of at least some of the most important policies put forward by jurisdictions would be welcome, it is beyond the scope of this thesis. The Climate Action Tracker, a consortium, currently tracks the existing emissions reduction policies and pledges of 32 countries representing about 80% of world emissions. It seeks to improve the cross-national comparability of action and highlight the emissions gap between these actions and what is required to achieve the objective of the Paris Agreement.

[2] The introduction of a national cap-and-trade system by China may change this state of affairs. China's GHG emissions have come to represent a growing share of world emissions over time, from 11% in 1990 to 27% in 2016 (Gutschow, Jeffery, and Gieseke, 2019). The system is due to start operating in 2020.

5.2 Political and technological inertia

5.2.1 Domestic hurdles

Equipped with this more robust assessment tool, we sought to uncover drivers of climate policy ambition in a systematic manner.

We first developed an improved understanding of the domestic political economy of carbon pricing policies. As was argued in chapter 2, limiting our focus to carbon pricing was justified by (i) the fact that political economy dynamics are specific to the nature and design of the policy tool at hand; (ii) carbon pricing policies have recently either been implemented in an increased number of jurisdictions or considered for implementation.

It became clear through our research that the implementation of carbon pricing mechanisms involved two distinct decisions, potentially affected by different dynamics: a decision as to whether or not to introduce such a policy, i.e. a participation decision, and a decision as to its stringency, i.e. price level and coverage. We therefore conducted our analysis by drawing a distinction between the dynamics of policy adoption and stringency. As noted earlier, this had non-trivial implications for our empirical strategy.

The results of the analysis in chapter 2 indicate that political economy constraints mostly affected the implementation of carbon pricing policies, with little identified effect on the actual stringency. The stringency of these policies was, however, identified as a highly persistent process. The analysis led us to two conclusions. First, the successful passage of carbon pricing legislation will either come with contemporaneous compensation of incumbent, CO_2-intensive, sectors or occur after their relative weakening. Second, if domestic political economy constraints continue to prevail, climate change mitigation strategies will require multiple instruments.

This chapter also offers a number of corollary insights, one of which being that a carbon pricing initiative by a single significant emitter can get us a long way in raising the world's average price tag on carbon and levelling the policy playing field. For instance, when China's emissions trading scheme comes online, an additional 9% of world emissions will be subject to a price (World Bank, 2019). Should these emissions be priced at, say, 5USD/tCO_2e, the world price would be raised by a third compared to its current level. This, however, would only account for the direct effect; but one could expect that such a move would trigger spillovers beyond China's borders, potentially inducing other jurisdictions to introduce or increase their own carbon price.

Another notable observation is that, until now, jurisdictions that did implement carbon pricing policies either had limited trade relationships with large emitters or acted jointly within the remit of relatively integrated trading blocks (e.g. the EU). This suggests that jurisdictions that consider implementation or strengthening of carbon pricing mechanisms ought to pay due attention to the nature and relative size of their trade relationships and consider carefully the implementation of policies such as carbon border adjustment to enhance the effectiveness of their domestic policy.

5.2.2 International dynamics

There is much to bet that these domestic developments will have an impact on other jurisdictions. This, in essence, is the motivation behind the approach taken in chapter 3. When developing climate change mitigation policies, jurisdictions should not only consider their domestic impact but also the ways through which they could provide additional incentives for other jurisdictions to follow suit. At a time where the world is looking for ways to raise collective climate policy ambition, these considerations cannot be eluded.

The analysis in chapter 3 suggests that processes of policy learning as well as technology deployment have been at play in the recent diffusion of climate policies. In particular, it suggested that these effects were related to the strength of bilateral relationships. Any (renewed) international effort aiming at strengthening climate policy regimes around the world should therefore seek to leverage existing pools of policy experience and technology, both local and global. Exactly how – and how quickly – this experience is shared among jurisdictions will determine the speed at which new carbon pricing mechanisms – and indeed climate change mitigation policies – will be adopted.

Yet, even though these mechanisms might be present for any jurisdiction, their strength will never be as great as when a larger emitter with significant trade (and other) ties with other jurisdictions takes the lead in providing credible policy or technological commitments.

5.2.3 Directed – and sustained – technological change

The role granted to technology (diffusion) in chapter 3 set the scene for the last chapter of the present thesis. If it is to play such a crucial role in raising climate policy ambition across jurisdictions, then gaining in depth understanding of technology development / innovation dynamics in countries that are likely to have a significant impact on the world's technological trajectory is of the essence. Moreover, on the road to a less GHG-intensive future, it is unlikely that restrictive emissions policies alone will provide a robust and politically viable insurance policy. Sustained innovation in GHG-free and GHG-abating technologies is required. In fact, breaking the fossil-fuel technological inertia might help to overcome domestic political deadlocks.

But decades of development of fossil fuel technologies make the shift to GHG-free ones difficult. It requires a resolute commitment to their development and deployment, not least by public authorities, until they have benefitted from sufficiently large learning effects so as to reduce their cost and face sufficiently large market demand to provide incentives for further innovation.

The analysis in chapter 4 indicated that the recent increase in innovation activity in electricity supply technologies originated overwhelmingly from small upstream Original Equipment Manufacturers, which were new (technological) entrants but that after a temporary surge, in part driven by policy intervention, UK-based innovation in GHG-abating electricity supply technologies has decreased again.

5.3 Raising collective climate policy ambition

Raising individual, and ultimately collective, climate policy ambition requires us to explore the dynamics governing both institutional and technological changes. We started our analysis with the intention to shed further light on these dynamics and each of the chapters in the present thesis make a contribution toward that goal. The conclusions reached in these chapters allow to draw some lessons about how to raise climate policy ambition.

In light of the insights gained from the analysis in chapters 2 to 4, we believe that any attempt at raising individual and collective ambition should be guided by the following principles. First, successful implementation of climate change mitigation policies requires an in-depth knowledge of the local political economy context. This is in order to design policies that circumvent potential opposition from incumbents whose income derives from GHG-emitting technologies.

In this regard, a salient observation made through the analysis is that jurisdictions that successfully introduced carbon pricing schemes directly addressed the economic loss that targeted sectors would suffer from, be it by supporting the development of new, less CO_2-intensive, technologies – and thereby *de facto* weakening opposition to more stringent policy prior to their attempted introduction – or by institutionalising the (financial) compensation of key actors in the affected sectors.

An instance of this approach is the strategy adopted in the European Union, which initiated support for renewable electricity generation technologies in 2001 and subsequently introduced its Emissions Trading System, with due compensation of covered incumbents through the initial grandfathering of emissions allowances.

Second, if political economy constraints continue to prevail and/or manifest themselves more strongly with respect to policies putting an explicit price on GHG emissions, weakening them in ways incompatible with emissions reduction targets, climate change mitigation strategies will require multiple instruments, both price and non-price based ones. For example, in the power sector, support schemes for the deployment of renewable electricity generation technologies such as feed-in-tariffs or renewable portfolio standards contribute to the reduction of emissions, yet present the political advantage of having a cost less visible to electricity consumers.

In an extreme case, one could think of carbon pricing mechanisms, especially quantity-based systems, as backstops to the rest of a jurisdiction's climate change mitigation policy portfolio. In such a case, emissions reduction is mostly triggered by other sectoral or economy-wide policies, while the quantity system ensures the creation of the appropriate price signal so that it stays within the carbon budget in case the other policies do not deliver as expected.

Third, in the quest to increase collective climate policy ambition, jurisdictions, especially the larger ones, should pay more attention to the external effects of their domestic policy decisions. Earlier literature and new evidence presented in this thesis suggests that (unilateral) domestic developments, especially by large economies, can spill-over beyond domestic borders. In particular, chapter 3 suggests that there could be strong external benefits to technological and institutional demonstration undertakings by (small groups of) countries. This is why early policy developments in the EU and more recent developments in countries like China are particularly important.

This last observation is aligned with a strand of literature exploring the role of club benefits in the development of effective international strategies to reduce global emissions (Victor, 2011; Victor, 2015). Indeed, a substantial body of work has argued that creating collective technological benefits (Carraro and Siniscalco, 1997; Buchner et al., 2005) or raising barriers (Nordhaus, 2015) could help overcome the international free-riding problem. Furthermore, recent discussion has focused on how initially timid institutional and technological developments (Pahle et al., 2018) or initiatives by initially small groups of countries (Falkner, 2015) can pave the way for more ambitious objectives and enlarged participation.

5.4 Further research

While the present thesis contributed towards answering the questions we set out at the start, it is by no means exhaustive and the present work could be extended in several ways.

First, for the sake of tractability, and because carbon pricing mechanisms constitute a key market-based policy tool of some jurisdictions, the present thesis limited the creation of a standardised assessment methodology to them. But it is important to keep in mind that carbon pricing mechanisms do not represent the only policy tool developed as part of jurisdictions' strategy to mitigate climate change. These policies co-exist with a number of other mechanisms aimed at incentivising the reduction of GHG emissions and/or the development of new GHG-free technologies. In this regard, I note that, despite economists arguing in favour of a carbon price as an efficient mechanism to achieve emissions reductions, most schemes have been introduced *in addition* or *in parallel* to (pre-existing) technology support policies. Looking forward, it is likely that climate policy making will continue to follow such pattern. This raises a number of questions with regard to (i) the role and design of carbon pricing mechanisms in policy environments where they play a "backstop role"; (ii) the role played by institutional paths allowing for the emergence of (more stringent) carbon pricing schemes (Pahle et al., 2018); (iii) the interaction between international and domestic climate policy environments. Further research in these directions could advance the implementation of GHG-reducing strategies and should constitute a priority for anyone with this objective.

In addition, as jurisdictions move forward with the decarbonisation of their economy, review their NDCs through the framework of the Paris Agreement and propose new tools to achieve them, it is of utmost importance that these be assessed according to commonly agreed and standardised methodologies. The work undertaken by the Climate Action Tracker is a step in that direction but further work is needed (Climate Action Tracker, 2019).

Second, the ECP in the present thesis has been used to analyse policy implementation. But it could also be used to analyse policy outcomes, i.e. the effect of carbon prices on actual emissions. This is the focus of an ongoing research project (joint with Ryan Rafaty) which seeks to uncover the effect of carbon prices on CO_2 emissions in 25 OECD economies between 1990 and 2016. Besides this, the emissions-weighted carbon price series currently runs between 1990 and 2018 but, with appropriate update of the underlying data to track institutional changes in covered schemes, could be extended as years go by.

Finally, policies sustaining innovation in GHG-free or GHG-abating technologies must be part of our strategy too and should remain in place until they lead to self-sustained streams of innovation in these technologies. The evidence available so far suggests that early policies aiming at fostering such innovation did trigger additional activity but that they did not necessarily lead to self-sustained innovation. This warrants a further investigation of factors and policy designs that could lead to a (self-)sustained stream of innovation in some of these technologies.

5.5 Concluding remark

This thesis presented clear evidence that, plagued by political economy factors and institutional inertia, the current international climate change mitigation regime falls short of the necessary insurance policy required to safeguard the climate equilibrium that makes the Earth hospitable to human life; but it also affirms that we have all the necessary tools and mechanisms to build it and, hence, that we need not lose this equilibrium. If we do, it would ensue from our free and deliberate choice.

Appendix A

Appendix to Chapter 2

A.1 Carbon prices - data sources and details

For each jurisdiction and each year we collect carbon price data in nominal local currency. Most jurisdictions quote the price of greenhouse gases (including CO_2) per tonne of CO_2e; others (essentially those with carbon taxes) express the carbon price per natural unit of the fuel. In the latter case, we convert the price to express it per tCO_2e using conversion factors from the World Resource Institute (World Resources Institute, 2015). All values are then converted into 2015 $US using the Official Exchange Rate (Local Currency Unit/$US) and inflation rate from the World Bank, 2016a.

A.1.1 Emissions Trading Schemes

TABLE A.1.1: ETSs prices – sources

Jurisdiction	*Price information*
EU-ETS	European Union emissions Allowances (EUA) futures price. Annual average of daily prices. Source: Bloomberg
Korea, Rep.	The market for Korean Allowance Units (KAUs) has been characterised by high illiquidity due to the absence of sellers amid concerns that the market is under-allocated. The last trade took place on March 15, 2016 at a price of $15.53. Source: South Korea Exchange
New Zealand	Annual average of daily spot prices of New Zealand Allowances (NZU). Source: Bloomberg.
Switzerland	As of 2015, no transaction of Swiss emissions allowances (CHU) had taken place over a centralised platform. Consequently, the price quoted in this study is the volume-weighted average price at auction. Source: Swiss Emissions Registry
California(-Quebec)	Annual average of daily California Carbon Allowances (CCA) futures contract price. Source: California Carbon Dashboard
RGGI	Volume-weighted annual average of spot transactions. Source: RGGI CO_2 Allowance Tracking System (COATS).

A.1.2 CO_2 taxes

Information on sectoral fuel tax rates has been retrieved from a wide range of sources. A full list of sources is available upon request. These sources include (but are not limited to): OECD Database on Instruments used for Environmental Policy (OECD, 2016a), International Energy

Agency Energy Price and Taxes publication (IEA, 2016a), jurisdictions' budget proposals (as in the case of, e.g., Norway or Denmark), customs' agencies documentation, academic journal articles, policy assessment reports.

A.1.3 Total CO_2 price (oil, natural gas)

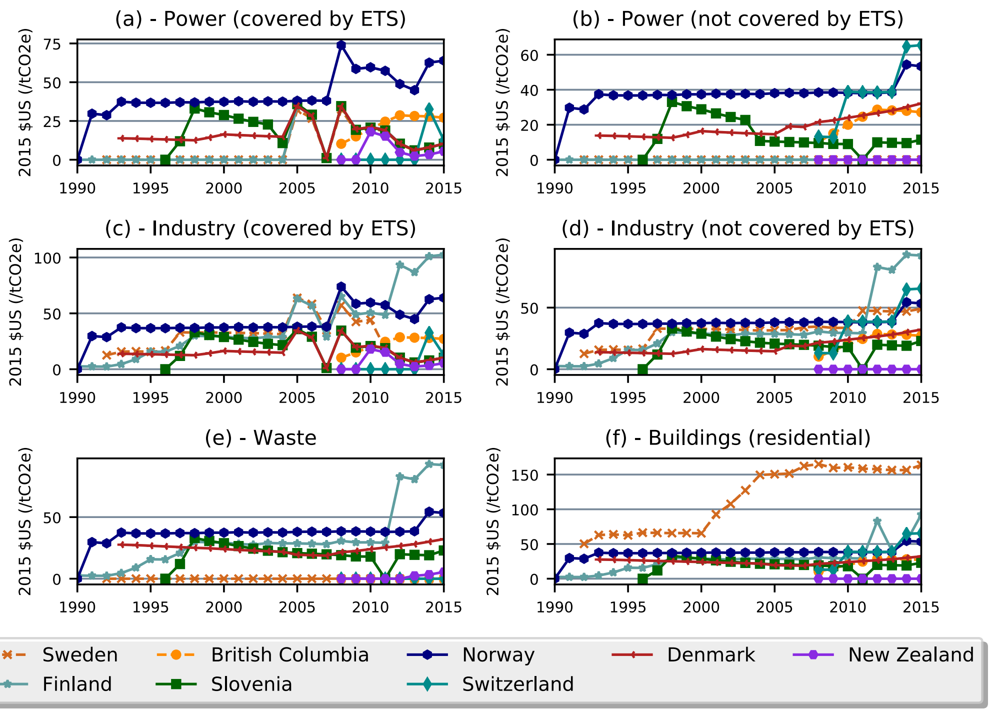


FIGURE A.1.1: Total carbon price over time – oil

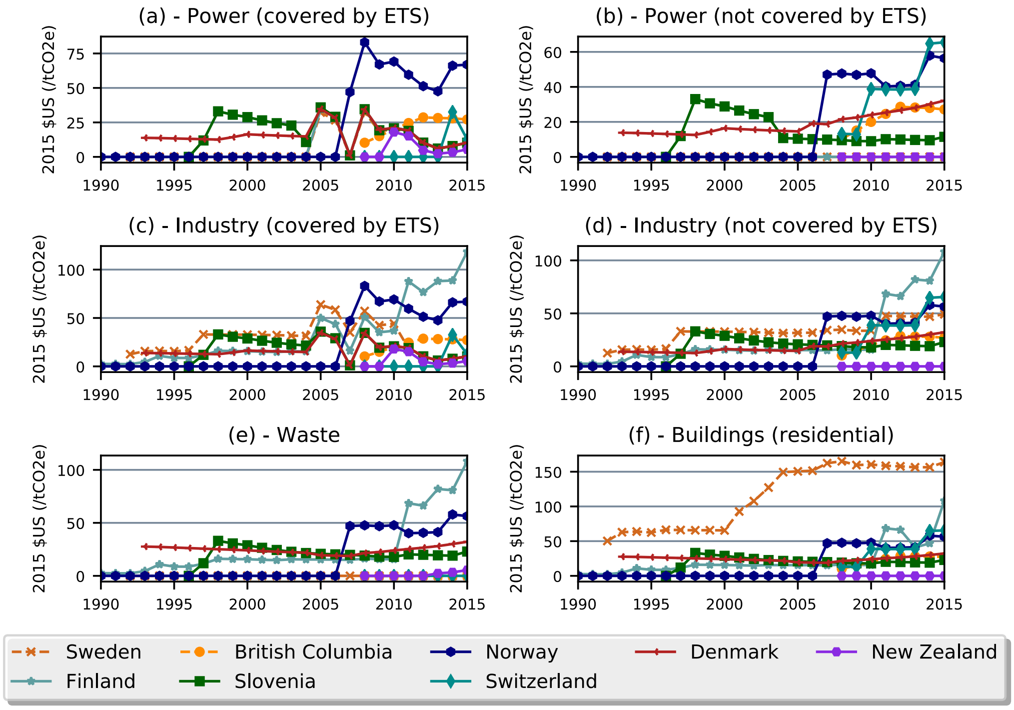


FIGURE A.1.2: Total carbon price over time – natural gas

A.2 Scheme's coverage

This methodological appendix further details the steps involved in the computation of the coverage figures. Computing coverage figures requires defining a sectoral disaggregation of the economy. For the sake of consistency with CAIT, 2015 and IEA, 2016b data, we adopt the sectoral disaggregation recommended by the IPCC, 2006 Guidelines for National Greenhouse Gases Inventories, which is itself based on the United Nations International Standards Industrial Classification (ISIC), Revision 4. Table A.2.1 summarises the sectoral disaggregation.

The scope of an emissions trading scheme is defined at the sectoral level regardless of the fuel from which CO_2 – and other GHG – emissions originate. Therefore, an emissions trading scheme requires the measurement of GHG emissions at the point of emission. The design of carbon (or any other GHG)-taxes is different in that they can applied to specific fuel(s) within particular sectors. The sectors subject to it are determined independently. The relevant physical unit to be measured in the case of a carbon tax is therefore the fuel consumption (and associated CO_2 emissions) at the user-fuel level. The fuel categories used in this study are: Coal/peat, Oil, Natural Gas.

The coverage information is recorded, for each jurisdiction and year, at the sector-fuel level as a binary variable (0 if the sector-fuel is not covered, 1 if it is). This coding is based on various sources, which vary from one country to the other. As for the carbon prices, a complete list of sources used to create the data points is available upon request. Table A.2.2 summarises the information recorded.

TABLE A.2.1: IPCC 2006 Sectoral disaggregation

IPCC sector name	**IPCC sector label**
Electricity Generation*	1.A.1.a.i
Combined heat and Power Generation*	1.A.1.a.ii
Manufacturing industries and construction*	1.A.2
Domestic Aviation	1.A.3.a.i
Road Transportation	1.A.3.b
Commercial and public services	1.A.4.a
Residential	1.A.4.b
Agriculture/forestry	1.A.4.c
Industrial Processes – cement	2.A.1
Waste	5

*In some countries and in some years, these sectors are covered by a tax and an emissions trading system. Sometimes, however, the tax schemes are designed to exempt those installations that are covered by the relevant ETS. Since CO_2 emissions data is disaggregated at the sector-fuel level and does not, within it, distinguish between those covered by the ETS and those that are not, it is not possible to account for this unless one makes an assumption about the proportion of emissions represented by the installations covered by the ETS.

TABLE A.2.2: Institutional design

	Carbon Tax	Emissions Trading System
Price signal	Tax rate (nominal - local currency)	(Spot/Futures) Allowance price (nominal - local currency)
Sectoral coverage	✓	✓
Fuel coverage	✓	n.a.
GHG-gas coverage	*	✓
Sector-fuel exemptions	✓	n.a.

*The only GHG covered by carbon taxes is obviously CO_2.
Note: For each jurisdiction and year, except price, all information is coded as a binary entry.

Calculating total coverage (as a share of total GHG emissions) of carbon pricing schemes at the level of a jurisdiction is then performed according to the following formula

$$Coverage_{i,t} = \frac{\sum_j \sum_k q_{i,t,j,k} \times \mathbb{1}_{i,t,j,k}}{q_{i,t}^{GHG}} \tag{A.21}$$

where $q_{i,t,j,k}$ represents jurisdiction i's CO_2 emissions from sector j arising from the combustion of fuel k in year t; $\mathbb{1}_{i,t,j,k}$ is an indicator variable taking value 1 if fuel k in sector j of country i in year t is covered by the scheme, 0 otherwise; $q_{i,t}^{GHG}$ is the total greenhouse gases emissions in jurisdiction i in year t. Note that in the case of ETSs, the aggregation starts at the sector level, since all fuels are, by definition, covered.

The calculations make use of sector and sector-fuel CO_2 emissions data. National jurisdictions: IEA, 2016b; US States: CAIT, 2015; Canadian Provinces and Territories: Statistics Canada, 2018. Total GHG emissions (excluding land use change) are taken from the CAIT, 2015 of the World Resources Institute.

A.3 Emissions-weighted Carbon Price methodology

Equipped with this information, the emissions-weighted price (ECP) can be computed at the sectoral or economy-wide level. In the former case, the weights are the emissions as a share of a sector's total GHG emissions; in the latter, the weights are the emissions as a share of the jurisdiction's total GHG emissions. Formally, the ECP of sector j of country i in year t is expressed as

$$ECP_{i,t,j} = \frac{\sum_k [\tau_{i,t,j,k} \times (q^{tax}_{i,t,j,k} + q^{ets,tax}_{i,t,j,k}) + p_{i,t,j,k} \times (q^{ets}_{i,t,j,k} + q^{ets,tax}_{i,t,j,k})]}{q^{GHG}_{i,t,j}} \tag{A.31}$$

where $\tau_{i,t,j,k}$ is the carbon tax rate applicable to fuel k in sector j of country i at time t, $q^{tax}_{i,t,j,k}$ is the amount of CO_2 emissions covered by a tax only, $p_{i,t,j}$ is the price of an emission permit, $q^{ets}_{i,t,j,k}$ is the amount of CO_2 emissions covered by an ETS, $q^{ets,tax}_{i,t,j,k}$ is the amount of CO_2 emissions covered by both an ETS and a tax and $q^{GHG}_{i,t,j}$ is the quantity of GHG emitted by sector j of country i in year t.

An economy-wide ECP is then computed as a weighted average of the carbon rates across sectors, where the weights are the quantity of emissions subject to each individual carbon rate:

$$ECP_{i,t} = \sum_j \left(ECP_{i,t,j} \times \gamma_{i,t,j}\right) \tag{A.32}$$

where $\gamma_{i,t}$ represents the GHG emissions of sector i as a share of the economy's (jurisdiction's) total GHG emissions, i.e. $\frac{q^{GHG}_{i,t,j}}{q^{GHG}_{i,t}}$. For the purpose of the present study, only the economy-wide ECP is computed and both a time-varying and fixed weights version of the ECP are calculated. The fixed-weights ECP uses 2013 emissions data.

A.4 Jurisdictions with carbon pricing policies

TABLE A.4.1: Jurisdictions with implemented carbon pricing schemes as of 2018

Jurisdiction	Emissions Trading	Carbon tax	ECP - 2015 (2015 $US)	ECP-2018 (2015 $US)
Austria	2005	-	4.04	7.9
Belgium	2005	-	3.15	6.18
Bulgaria	2007	-	5.64	11.12
Cyprus	2005	-	4.7	9.8
Czech Republic	2005	-	6.06	11.89
Denmark	2005	1992	16.07	8.09
Estonia	2005	2000	8.48	13.34
Finland	2005	1990	35.53	43.95
France	2005	2014	6.49	17.32
Germany	2005	-	5.07	9.96
Greece	2005	-	5.51	11.04
Hungary	2005	-	3.28	6.45
Iceland	2008	2010	6.68	19
Ireland	2005	2010	10.29	12.81
Italy	2005	-	3.89	7.66
Japan	-	2012	1.24	1.87
Kazakhstan	2013	-	0.01	†
Korea, Rep.	2015		6.78	14.11
Latvia	2005	1995	2.34	4.61
Liechtenstein	2008	-		
Lithuania	2005	-	2.73	5.42
Luxembourg	2005	-	1.44	2.81
Malta	2005	-	5.73	11.15
Mexico	-	2014	1.42	1.42
Netherlands	2005	-	4.61	9.02
New Zealand	2008	-	1.91	6.32
Norway	2007	1991	40.85	39.39
Poland	2005	1990	5.4	10.73
Portugal	2005	2015	7.36	12.59
Romania	2007	-	4.15	8.23
Slovak Republic	2005	-	4.86	9.61
Slovenia	2005	1996	12.87	16.93
Spain	2005	-	4.21	8.32
Sweden	2005	1991	87.86	91.3
Switzerland	2008	2008	17.3	
United Kingdom	2005	2013	12.16	16.32
Alberta*	2007	-		
Beijing	2013	-	n.a.	
British Columbia	-	2008	16.85	19.66
California	2009	-	9.66	11.54
Chongqing	2014	-	n.a.	
Connecticut	2009	-	1.09	0.75
Delaware	2009	-	1.74	1.20
Guangdong	2013	-	n.a.	
Hubei	2013	-	n.a.	
Kyoto	2011	-	†	
Maine	2009	-	0.5	0.35
Maryland	2009	-	1.57	1.08
Massachusetts	2009	-	1.09	0.75
New Hampshire	2009	-	1.4	0.97
New York	2009	-	0.99	0.68
Quebec	2013	-	6.7	7.93
Rhode Island	2009	-	1.62	1.12
Saitama	2011	-	†	
Shanghai	2013	-	n.a.	
Shenzhen	2013	-	n.a.	
Tianjin	2013	-	n.a.	
Tokyo	2010	-	†	
Vermont	2009	-	0.02	0.01

†: missing information at the time of writing – Chile: 2017; South Africa: 2016; New Jersey's scheme was discontinued in 2011, Australia's in 2012.

Appendix B

Appendix to Chapter 3

B.1 Abatement function

Define the abatement technology as $A(e^P, v^A)$ where e^P is the potential amount of pollution produced and v^A is the (absolute) amount of resources allocated to abatement. $A(.)$ is a CRS activity. Then, $e = e^P - A(e^P, v^A) \Leftrightarrow e = e^P(1 - A(1, v^A/e^P))$. Now, recall that without abatement activity, $e^P = x = \Omega B(.)$ and that $v^A/B(.) = \phi$. Hence $e = \Omega B(.)(1 - A(1, \phi))$ where we have defined $(1 - A(1, \phi))$ as $\chi(\phi)$.

B.2 Pollution as input

We start by rearranging equation 3.3 to obtain an explicit analytical expression of abatement effort, $\phi = \chi^{-1}[e/(\Omega B(K_x, L_x))]$. Substituting this expression in equation 3.2 we can then write

$$x = \left(1 - \chi^{-1}\left[\frac{e}{\Omega B(K_x, L_x)}\right]\right) B(K_x, L_x) \tag{B.2.1}$$

This clearly shows that net production of the dirty good depends on (i) potential production, which in turn depends on how much resources the economy allocates to the dirty sector; (ii) the number of emission units available to the sector. Importantly, the effect of both factors on net production depends on their effect on abatement effort.

Hence, we next show that $\partial\chi^{-1}(.)/\partial e < 0$ and $\partial\chi^{-1}(.)/\partial B(.) > 0$, which implies that an increase in available emission units lowers abatement effort and raises net production. Indeed, define $C \equiv e/B(K_x, L_x)$. By the inverse function theorem, we know that $\chi^{-1}(.)$ satisfies $\partial\chi^{-1}(.)/\partial C < 0$. By definition of C, we have $\partial C/\partial e > 0$ and $\partial C/\partial B(.) < 0$. Hence we must have $\partial\chi^{-1}(.)/\partial e < 0, \partial\chi^{-1}(.)/\partial B(.) > 0$.[1]

[1] This leads to two interesting observations: first, an increase in emissions allowance raises net output of good x; second, an increase in potential output $B(.)$ affects net output via a production channel and an abatement channel. The first one straightforwardly tends to raise production, higher potential production leads to higher actual production. The second tends to lower actual production and is more indirect: $\chi(\phi)$ gives the abatement efforts as a function of the ratio of unabated to total potential emissions. Hence when potential production (and emissions) increases, that ratio decreases, for a given level of actual emissions. This requires an increase in abatement efforts which, in turn depresses net output. Whether one or the other effect dominates is eventually an empirical question but it seems plausible to assume that the former outweighs the latter.

Finally, equation B.2.1 is simplified if we define the abatement function as $\chi(\phi) = (1-\phi)^{1/\alpha}$. This expression satisfies the properties imposed earlier on the abatement technology and implies that there are diminishing returns to abatement effort. We then have $\phi = 1 - \left(\frac{e}{\Omega B(K_x,L_x)}\right)$ and we can rewrite B.2.1 as

$$x = \left(\frac{e}{\Omega}\right)^{\alpha} B(K_x, L_x)^{1-\alpha} \tag{B.2.2}$$

B.3 Firm's profit maximisation

The firm in the Y sector does not pollute and the profit function is thus

$$\pi^y = pF(K_y, L_y) - wL_y - rK_y \tag{B.3.1}$$

In the X (dirty) sector,

$$\begin{aligned} \pi^x &= pX(K_x, L_x) - wL_x - rK_x - \delta e \\ &= \underbrace{p(1-\alpha\Omega)}_{\text{net producer price}} \; X(K_x, L_x) - wL_x - rK_x \end{aligned} \tag{B.3.2}$$

We derive the second equality by substituting e for its value, given by equation 3.5, and rearranging the terms. Next, recalling that

$$\frac{\delta \frac{e}{\Omega}}{px} = \alpha \tag{B.3.3}$$

and that $0 < \alpha < 1$ and $0 < \Omega \leq 1$ it is easy to see that $\alpha\Omega$ represents the share of pollution payments in total value added. We note two observations. First, assuming constant α, a decrease in the share of pollution payments can be interpreted as reflecting a decrease in Ω, i.e. an improvement in abatement technology. Second, as Ω decreases, the net revenue (i.e. revenue net of pollution permit payment) increases.

This, together with the relative price of the good, determines the allocation of resources between sectors. Indeed, recalling our perfect competition assumption, Euler's theorem, and the fact that labour and capital are inelastically supplied, we have

$$F_K = p(1-\alpha\Omega)X_K = r\, ;\; F_L = p(1-\alpha\Omega)X_L = w$$

where X_K, X_L and F_K, F_L denote the marginal productivity of factors in sectors X and Y, respectively. That is, factors of production are remunerated at the value of their marginal product which, since both sectors trade inputs in the same markets, is equalised across sectors. Rearranging the above yields,

$$\frac{F_K}{X_K} = \frac{F_L}{X_L} = p(1-\alpha\Omega) \equiv S \tag{B.3.4}$$

This is the equilibrium resource allocation condition.

Based on that condition, we note that when Ω decreases (i.e. abatement technology improves), "payments to pollution" per unit of dirty good produced decrease, making the dirty good sector relatively more attractive, and inducing a reallocation of the economy's resources from the clean to the dirty good sector. In other words, an improvement in the abatement technology induces a change in the *composition* of the economy.

Finally, equation B.3.4 provides an interesting result: the effect of a change in relative price on resource allocation varies with the abatement technology Ω. That is, define Ω^{high} and Ω^{low}, denoting *poor* and *good* abatement technology, respectively. Then

$$\left.\frac{\partial S}{\partial p}\right|_{\Omega^{high}} < \left.\frac{\partial S}{\partial p}\right|_{\Omega^{low}} \tag{B.3.5}$$

When a jurisdiction has good abatement technology, a change in the relative price of the dirty good will induce a larger reallocation of resources from the clean to the dirty sector.

B.4 Prices, emission intensity and abatement efforts

It now becomes possible to derive an expression of ϕ in terms of prices. Using equation 3.5 to note that total emissions are equal to $e = ix$, we can rewrite the production function B.2.2 as

$$x = \left(\frac{ix}{\Omega}\right)^{\alpha} B(K_x, L_x)^{1-\alpha}$$

Yet, we also know that $x = (1-\phi)B(K_x, L_x)$. Hence

$$i = (1-\phi)^{(1-\alpha)/\alpha}\Omega \tag{B.4.1}$$

which suggests that the emission intensity of the economy decreases in two cases: when more resources are devoted to abatement and when the abatement technology improves. Now, substituting i for its expression in equation (3.5) yields

$$\frac{\alpha\Omega p}{\delta} = (1-\phi)^{(1-\alpha)/\alpha}\Omega$$

and we can therefore write

$$\phi = 1 - \left(\frac{\alpha p}{\delta}\right)^{\alpha/(1-\alpha)} \tag{B.4.2}$$

As it turns out, abatement effort is independent from Ω, the abatement technology quality. However, an improvement in abatement technology might affect equilibrium abatement effort through its effect on equilibrium emissions price.

In a general equilibrium context, the total effect of a (positive) technological change in abatement comes in two ways. First, for a given (equilibrium) price of emissions, pollution payments per unit of dirty good decreases, inducing a shift of inputs from the clean to the dirty sector and hence stimulating production in the latter – this is the *composition* effect identified in B.2, which tends to raise pollution demand. Second, the technological improvement also induces a reduction in the emission intensity of the dirty sector – a *technique* effect, which tends to reduce pollution demand.

If the technique effect is stronger than the composition effect, then an improvement in abatement technology will lead to a decrease in pollution demand. The ensuing downward adjustment in equilibrium emissions price δ will induce a decrease in abatement effort.

B.5 Regulatory threshold

The present discussion is based on Copeland and Taylor, 2003. We adopt a constant relative risk aversion utility function for the consumption component of utility and a constant marginal disutility of emissions. Therefore, the indirect utility function becomes

$$V(p, I, E) = \frac{[I/\omega(\mathbf{p})]^{1-\eta}}{1-\eta} - \lambda E, \text{ with } \eta \neq 1$$

where $E = E_{-i} + e_i$. For simplicity, it is assumed that the economy produces only one (dirty) good so that income is

$$I = p\left(\frac{e_i}{\Omega}\right)^{\alpha} B(K, L)^{1-\alpha}$$

To find equilibrium emissions we derive the inverse pollution demand

$$\alpha p\left(\frac{e_i}{\Omega}\right)^{\alpha-1} \Omega^{-1} B(K, L)^{1-\alpha} \Leftrightarrow \alpha \underbrace{p\left(\frac{e_i}{\Omega}\right)^{\alpha} B(K, L)^{1-\alpha}}_{=I} \left(\frac{E_i}{\Omega}\right)^{-1} \Omega^{-1} \Leftrightarrow \frac{\alpha}{e_i} I \tag{B.5.1}$$

and the pollution supply

$$-\frac{V_{E_i}}{V_R} \Leftrightarrow -\frac{-\lambda}{\left[\frac{(I/\beta(p))^{-\eta}}{\beta(p)}\right]} \Leftrightarrow -\frac{\lambda\beta(p)}{R^{-\eta}} \tag{B.5.2}$$

Equating B.5.1 and B.5.2 and solving for e_i yields

$$e_i = \frac{\alpha}{\lambda} R^{1-\eta} \tag{B.5.3}$$

Substituting B.5.3 in the utility function leads to

$$V^R(p, I, E) = \left[\frac{1}{1-\eta} - \alpha\right] R^{1-\eta} - \lambda E_{-i} \tag{B.5.4}$$

At this stage, we can note that if the economy incurs a fixed cost of regulation, income will be reduced. Indeed, suppose that regulation is expected to require $(\bar{K}, \bar{L})$ of resources (i.e. $\mathbb{E}(\bar{K}, \bar{L}) \equiv \Phi$), then the expected resources available for production are $(K - \bar{K}, L - \bar{L})$, the potential production becomes $B^R \equiv B(K - \bar{K}, L - \bar{L})$ and income is

$$I^R = p\left(\frac{e_i}{\Omega}\right)^{\alpha} (B^R)^{1-\alpha}$$

If the expected cost of regulation decreases, then income increases following an increase in potential output. As a result, utility under regulation is now higher at any level of initial endowment in (K, L) of the economy. Formally, we have $\partial V^R / \partial \Phi < 0$.

In the no regulation case, no abatement takes place so that real income is equal to (potential) output and emissions are directly proportional to it. Utility is then defined as

$$V^{NR}(p, I, E) = \frac{R^{1-\eta}}{(1-\eta)} - \lambda R - \lambda E_{-i} \tag{B.5.5}$$

It can be shown that B.5.5 first rises and then declines with real income. V^{NR} increases over $[0, \sqrt[\eta]{1/\lambda}[$ and decreases over $]\sqrt[\eta]{1/\lambda}, +\infty$. Indeed, $\frac{\partial V^{NR}}{\partial R} = R^{-\eta} - \lambda$ is positive over $[0, \sqrt[\eta]{1/\lambda}[$, equals 0 in $R = \sqrt[\eta]{1/\lambda}$ and is negative over $]\sqrt[\eta]{1/\lambda}, +\infty$. Since V^R is monotonically increasing over the interval $[0, +\infty$, there exists a unique level of income such that $V^R = V^{NR}$ and beyond which $V^R > V^{NR}$. That is, we can write $\bar{I} \equiv V^R = V^{NR}$. Given $\partial V^R / \partial \Phi < 0$, we have $\partial \bar{I} / \partial \Phi > 0$.

Appendix C

Appendix to Chapter 4

C.1 Patent data (and patents search)

Our main proxy for patenting activity in the UK is the number of patent applications contained in the EPO Worldwide Statistical Patents Database, version of Autumn 2018 (European Patent Office, 2018). We downloaded patents which had at least one IPC code starting with 'B','F','G', or 'H' for the years 1955-2017.[1] This represents 354760 patents.

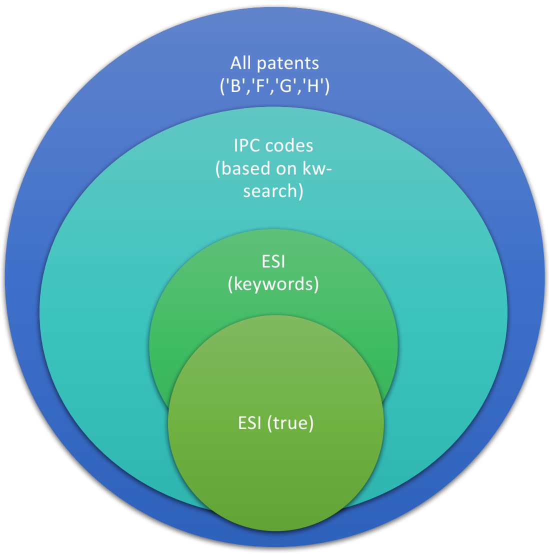


FIGURE C.1.1: Patent sets

ML search To use the classifier on the said set, we need to create a training sample based on the text of patents related to electricity supply technologies and those related to other technologies. The approach taken to construct the sample and train the classifier builds on Kreuchauff and Korzinov, 2017 and involves the following steps:

[1] As mentioned earlier, we downloaded filings up to 2017 but truncated our sample to 2016 to account for a lag between filing and actual recording in the database. This covers all the IPC codes pertaining to fossil fuel and renewable electricity generation technologies, as identified in Lanzi, 2010 and Johnstone, Haščič, and Popp, 2010 respectively, with the exception of the following codes: B01J8/20-22, C10J;C10L 5/40-48,C10L 1,C10L 3,C10L 5,E04D 13/18

1. The classifier is trained on a sample of 240 patents, which includes 126 patents pertaining to electricity supply technologies and 116 patents pertaining to other technologies. This sample is constructed as follows. First, we randomly select 200 patents from the patent ensemble comprising all patents with at least one IPC code in the list of those associated with the patents identified by the keywords-based search and 130 patents from the sample identified by the keywords search.[2] The titles and abstracts of all 330 patents were read so as to manually classify the them between (i) electricity supply technologies and (ii) other technologies. In the sample of patents drawn from the keywords-based ensemble, we identified 14 patents that were "false positives" whereas in the IPC ensemble we identified 22 "false negatives", which left us with 138 patents identified as belonging to the former category and 192 identified as belonging to the latter. In our training sample, we included all "false positives" of the keywords-based ensemble and 100 non electricity supply related patents of the IPC ensemble, as well as all "false negatives" of the IPC ensemble and all electricity supply related patents of the keywords-based ensemble. This, removing duplicates, left us with 114 patents pertaining to technologies unrelated to electricity supply and 126 patents pertaining to electricity supply technologies. These 240 patents constitute our training sample.

2. The text of the 240 patents titles and abstracts is prepared for classification

   (a) Structure the text data (application title and abstract). That is, for for each patent application: (i) merge patent title and abstract in one element and split into a single list of words; (ii) transform all string characters into lowercase characters; (iii) remove blank entries, stop words, empty spaces and numbers; (iv) extract the stem of each word; (v) Generate n-grams;

   (b) Derive normalised word and n-gram frequencies (across all patent applications)

   (c) Select features for classification. Not all features identified are carry meaningful information from a classification perspective. In other words, they add noise. Following Kreuchauff and Korzinov, 2017, we kept only the features that appeared in at least 2% of the patent applications.

3. Train our random forest classifier on a (training) sample. This comprised three iterative steps (common to almost any machine learning approach): training of the model, its evaluation, and optimisation. Finally, the classifier with the best model fit was applied to some test data;

4. Apply trained classifier to full sample.

[2] The sample size is determined by the selection algorithm. We aimed for a sample size as close to 100 as possible, representative of the keyword search queries performed in proportion of the patents identified by each of them in the keywords ensemble, and under the constraint that at least one patent from each query.

TABLE C.1.1: Classification report

	Precision	Recall	f1 score	No of patents in test set (support)
Non ESI	0.77	1	0.87	23
ESI	1	0.81	0.9	37
Avg./total	0.91	0.88	0.88	60

All steps describe above were performed using the python programming language and the following libraries: pandas (for data handling), nltk (for natural language processing), scikit-learn (for machine learning). Note that as a by-product of our "augmented" keywords-based search we also get a sample of patents selected only based on keywords.

Other List of actors for which at least one patent filing entry was returned by our search

TABLE C.1.2: List of actors

BRITISH GAS TRADING
BRITISH NUCLEAR FUELS
CENTRAL ELECTRICITY GENERATING BOARD
CENTRAL ELECTRICITY GENERATING BOARD MARTIN R E
CENTRAL ELECTRICITY GENERATING BOARDS
CENTRICA CONNECTED HOME
CO-OPERATIVE ENERGY
DRAX POWER
EA TECHNOLOGY
ELECTRICITY COUNCIL
ELECTRICITY COUNCIL HODGETT D L FUNG H
ELECTRICITY COUNCIL ROBINSON G
ELECTRICITY COUNCIL THE
FLEXITRICITY
INNOGY
INNOGY TECHNOLOGY VENTURES
LONDON UNDERGROUND
MAGNOX ELECTRIC
NATIONAL GRID COMPANY
NATIONAL POWER
NORTH OF SCOTLAND HYDRO-ELECTRIC BOARD
NORTHERN IRELAND ELECTRICITY
NPOWER
POWERGEN
RWE INNOGY
SCOTTISH HYDRO-ELECTRIC
SCOTTISH NUCLEAR
SCOTTISH POWER
SOUTH OF SCOTLAND ELECTRICITY BOARD
UNITED KINGDOM ATOMIC ENERGY AUTHORITY

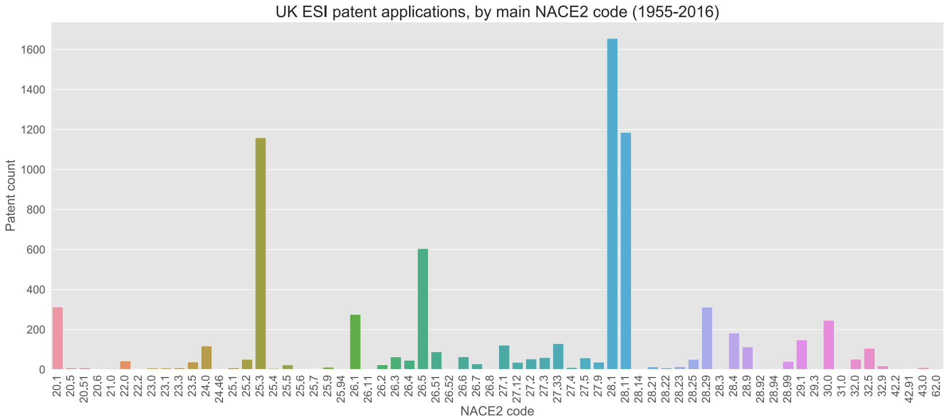


FIGURE C.1.2: UK ESI patent applications, by main NACE2 class
This figure excludes filings by individuals. Including these filings changes the count of patents in each NACE category but does not change the proportional distribution across them. Within each class, counts are based on the weighted-average count, i.e. 1 over the number of classes with which each patent is associated.

C.2 Database queries

C.2.1 PATSTAT online

Below are the SQL queries used to query the PATSTAT database via the online platform PATSTAT online. PATSTAT contains bibliographical and legal status data originating from 90 patent issuing authorities, including regional patent offices like the EPO.

The first query is designed to retrieve all PATSTAT tables (except table *tls203_appln_abstr* containing the patent abstracts) pertaining to patent applications filed between 1955 and 2017 and with at least one technology code starting with H, G, F or B . In practice, the query is executed separately for five different time periods: 1955-1964, 1965-1973, 1974-1985, 1986-1996, 1997-2017. The start and end years of these periods are substituted for YEAR_START and YEAR_END in the code below.

The second query is designed to retrieve the abstracts of all patents identified by the first query.

```
-------------Retrieving Patent Applications and Titles----------------------
SELECT distinct app.[appln_id]
      /*,app.[appln_auth]
      ,app.[appln_nr]
      ,app.[appln_kind]
      ,app.[appln_filing_date]
      ,app.[appln_filing_year]
      ,app.[appln_nr_original]
      ,app.[ipr_type]
      ,app.[earliest_filing_id]
  ,dbo.GROUP_CONCAT_DS(DISTINCT ipc_class_Symbol ,N' ,' ,1) IPC */
```

```
FROM  [patstat2018a].[dbo].[tls201_appln] app
join tls203_appln_abstr on app.appln_id = tls203_appln_abstr.appln_id
join tls209_appln_ipc on app.appln_id = tls209_appln_ipc.appln_id
       and left(ipc_class_symbol, 1) in ('H','G','F','B')
where app.appln_auth = 'GB' and app.appln_filing_year between YEAR_START and YEAR_END
        and (app.earliest_filing_id = app.appln_id or app.appln_id in
        (select tls204_appln_prior.appln_id from tls204_appln_prior join tls201_appln
        as prior on tls204_appln_prior.prior_appln_id = prior.appln_id
        where appln_auth = 'GB'))
and app.appln_id < 900000000

order by app.appln_id desc

-------------Retrieving Patent Abstracts----------------------
SELECT distinct top 500000 app_abstr.[appln_id], app_abstr.[appln_abstract]
      /*,app.[appln_auth]
      ,app.[appln_nr]
      ,app.[appln_kind]
      ,app.[appln_filing_date]
      ,app.[appln_filing_year]
      ,app.[appln_nr_original]
      ,app.[ipr_type]
      ,app.[earliest_filing_id]
  ,dbo.GROUP_CONCAT_DS(DISTINCT ipc_class_Symbol ,N' ,' ,1) IPC */

FROM  [patstat2018a].[dbo].[tls203_appln_abstr] app_abstr
join tls201_appln on app_abstr.appln_id = tls201_appln.appln_id
join tls209_appln_ipc on app_abstr.appln_id = tls209_appln_ipc.appln_id
       and left(ipc_class_symbol, 1) in ('H','G','F','B')
where tls201_appln.appln_auth = 'GB'
and tls201_appln.appln_filing_year between 1955 and 2017
and (tls201_appln.earliest_filing_id = tls201_appln.appln_id
        or tls201_appln.appln_id in
       (select tls204_appln_prior.appln_id from tls204_appln_prior
       join tls201_appln  as prior on tls204_appln_prior.prior_appln_id = prior.appln_id
       where appln_auth = 'GB'))
and app_abstr.appln_id < 900000000

order by app_abstr.appln_id desc
```

C.2.2 FAME

The FAME database interface allows to perform company searches based on their Company Registration Number (CRN). In particular, it allows to upload a list of CRN on the interface and retrieve information on the associated companies. The extracted information includes: Global Ultimate Owner information (name, address, NACE Industrial classification code), number of employees, turnover, R-D expenditures, primary and secondary NACE code, date of incorporation.

C.3 Technology codes

TABLE C.3.3: IPC/CPC Technology codes

Technology	IPC class	CPC class	Class title	Source
Electricity generation				
Fossil Fuel				
	F01K			Lanzi, 2010
	F02C			Lanzi, 2010
	F02G			Lanzi, 2010
	F22			Lanzi, 2010
	F23			Lanzi, 2010
	F27			Lanzi, 2010
Efficiency-enhancing fossil fuel				
	F23C5/24			Lanzi, 2010
	F23C6			Lanzi, 2010
	F23B10			Lanzi, 2010
	F23B30			Lanzi, 2010
	F23B70			Lanzi, 2010
	F23B80			Lanzi, 2010
	F23D1			Lanzi, 2010
	F23D7			Lanzi, 2010
	F23D17			Lanzi, 2010
	B01J8/20-22			Lanzi, 2010
	B01J8/24-30			Lanzi, 2010
	F27B15			Lanzi, 2010
	F23C10			Lanzi, 2010
	F22B31			Lanzi, 2010
	F22B33/14-16			Lanzi, 2010
	F01K3			Lanzi, 2010
	F01K5			Lanzi, 2010
	F01K23			Lanzi, 2010
	F22G			Lanzi, 2010
	F02C7/08-105			Lanzi, 2010
	F02C7/12-143			Lanzi, 2010
	F02C7/30			Lanzi, 2010
	F01K23/02-10			Lanzi, 2010
	F02C3/20-36			Lanzi, 2010
	F02C6/10-12			Lanzi, 2010
	F02B1/12-14			Lanzi, 2010
	F02B3/06-10			Lanzi, 2010
	F02B7			Lanzi, 2010
	F02B11			Lanzi, 2010
	F02B13/02-04			Lanzi, 2010
	F02B49			Lanzi, 2010
	F01K17/06			Lanzi, 2010
	F01K27			Lanzi, 2010
	F02C6/18			Lanzi, 2010
	F02G5			Lanzi, 2010
	F25B27/02			Lanzi, 2010
Renewables		Y02E 10		European Patent Office, 2013
	F03D1-F03D11			Johnstone, Haščič, and Popp, 2010
	F03G6			Johnstone, Haščič, and Popp, 2010
	F24J2			Johnstone, Haščič, and Popp, 2010
	H01L27/42			Johnstone, Haščič, and Popp, 2010
	H01L31/04/78			Johnstone, Haščič, and Popp, 2010
	H02N6			Johnstone, Haščič, and Popp, 2010
	E04D13/18			Johnstone, Haščič, and Popp, 2010
	F24J3			Johnstone, Haščič, and Popp, 2010
	F03G4			Johnstone, Haščič, and Popp, 2010
	F03G7/04			Johnstone, Haščič, and Popp, 2010
	E02B9/08			Johnstone, Haščič, and Popp, 2010
	F03B13/10-26			Johnstone, Haščič, and Popp, 2010
	F03G7/05			Johnstone, Haščič, and Popp, 2010
Nuclear		Y02E 30		European Patent Office, 2013
	G21F			Authors
	G21G			Authors
	G21K			Authors
Jet and gas engine turbines	B64C			Authors
	B64D			Authors
	F01D			Authors
	F02K			Authors
	F04D			Authors
Electricity transmission and distribution				
	H01B			Authors
	H01G			Authors
	H01H			Authors
	H01L 39			Authors
	H01T			Authors
	H01R			Authors
	H02G			Authors

TABLE C.3.4: IPC/CPC Technology codes (cont.)

Technology	IPC class	CPC class	Class title	Source
Other technologies				
Instruments	G01			Authors
	G02			Authors
	G03			Authors
	G06			Authors
	G08			Authors
Energy storage	H02J			Authors
	H01M			Authors
Pollution control	B01D			Authors
Equipment manufacturing methods	B21C			Authors
	B22F			Authors
	B25J			Authors
	B29C			Authors
Other general engineering	F01D1			Authors
	F01D9			Authors
Other technology classes filed by UK AEA or EC	B01J			Authors
	H01F			Authors
				Authors
				Authors
				Authors
Other	F15C			Authors
	F16			Authors

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